

Essays on Government Policy and the Allocation of Resources

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Dedication

To Fausto, Olga, Brigitte, Carolina, Marilú, Gonzalo, Jaime, Olguita, and Consuelo. Thank you for always motivating me to strive for more.

Abstract

This dissertation studies the effects of government policies on macroeconomic aggregates. Chapter 1 evaluates the impact of occupational licensing on consumer welfare, the allocation of labor, and the wage premium between licensed and unlicensed workers. In the United States, workers must undergo training and pay a fee to become licensed. Licensing policy protects consumers by alleviating an information asymmetry in the product market. However, it is an entry barrier that distorts the occupational choice of workers in the labor market. To analyze this trade-off, a framework with adverse selection in the product market and occupational choice in the labor market is developed. The model is calibrated to the US labor market using worker level micro-data. Removing licensing training requirements leads to a 4 percent reduction in consumer welfare and the wage premium falls by more than half.

Chapter 2 is written jointly with Marcos Dinerstein. This chapter studies the effect of corporate taxes on aggregate total factor productivity (TFP). Using Chilean manufacturing data, this chapter documents that there is large dispersion in the effective tax rate and there is a large mass of firms facing a 0 percent tax rate. These features are used to develop and discipline a standard monopolistic competition model with corporate tax rates. When corporate taxes are eliminated, TFP increases between 4 and 11 percent. However, when all firms face the Chilean statutory tax rate, TFP decreases despite the fact that the dispersion in tax rates is eliminated.

Chapter 3 is coauthored with Guillermo Cabral. This chapter analyzes the role of demographics in explaining the trends of real variables after the Great Recession. An important reason why demographics play an important role during the crisis's recovery period is that the Great Recession coincides with the "baby boomers" entering retirement age. This chapter documents that employment is converging to a different trend relative to its pre-crisis long term trend. A standard growth model with demographic features is calibrated in order to quantify the effect of demographics on output after the Great Recession. Demographics account for 35% of the change in the trend of output after 2008.

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1 The Welfare and Labor Market Effects of Occupational Licensing

1.1 Introduction

Occupational licensing and its impact on the United States economy is at the heart of the current policy agenda. Close to 25 percent of workers in the United States are required to have an occupational license in order to perform their job. Furthermore, as highlighted by Carpenter, Knepper, Erickson, and Ross (2012) and Kleiner and Krueger (2013), the share of licensed workers in the US labor market has increased fivefold since the 1950s. Understanding the social benefits and costs of occupational licensing are topics of much debate as this policy has implications for consumer welfare and for labor market outcomes.

Licensing policy generates a trade-off. On the one hand, licensing can have a positive effect on consumer welfare by alleviating an information asymmetry in the markets of goods and services. In particular, when consumers purchase goods from producers, consumers are less informed than the producers about the quality of the product. On the other hand, licensing policy acts as a barrier to entry that prevents individuals from working in licensed occupations. Workers that wish to enter licensed professions are typically required to pay a licensing fee and undergo occupation specific training. Hence, licensing lowers incentives for workers to enter licensed occupations as it is costly in terms of resources, time, and effort.

This chapter studies the effect of occupational licensing on welfare, the allocation of labor, and the wage premium between licensed and unlicensed workers. My first contribution is to develop a framework with the key ingredients that highlight the trade-off generated by licensing policy. Earlier literature pioneered by Leland (1979) and Shapiro (1986) carried out theoretical analyses of the effect of licensing policy on consumer welfare. They determine that licensing can be welfare improving in the presence of information asymmetries in the product market, since buyers know less about the quality of goods relative to sellers. I build on this earlier theoretical literature by developing a framework with adverse selection in the product market, occupational choice in the labor market, and a licensing policy composed of a fee and training. In the model, changes in the licensing policy affect consumer welfare through two forces. As licensing requirements are higher, the quality of the goods that are produced increases, which raises welfare. However, less resources are allocated towards consumption and more towards license costs, which reduces welfare.

My second contribution is to quantify the welfare and labor market effects of reforming occupational licensing in the US. For this, I estimate the parameters of the theoretical model to match moments of the US labor market, focusing only on occupations that are predominantly composed of workers with less than college education. The conventional view of the literature on the effects of occupational licensing policy on consumer welfare is that the social costs are larger than the benefits. However, the literature's assessment of these benefits has been limited. I provide the first estimates of the welfare consequences of occupational licensing within a theoretical framework that explicitly models a market failure: adverse selection in the product market. I find that removing the training requirements of licensing results in a reduction of 3.9 percent in consumer welfare. Although consumption rises as lower resources are allocated towards license costs, lower quality goods are produced resulting in the consumer welfare loss. Hence, I find that the quality effect dominates when training requirements are removed.

In addition, this chapter contributes to the vast literature on wage differences between licensed and unlicensed workers. Using the calibrated model, I decompose the wage premium between licensed and unlicensed workers into components explained by the composition of ability of workers between occupations, occupation-specific skills obtained from licensing training requirements, and information rents. I find that under different licensing training requirements, changes in the wage premium are explained mainly by changes in the composition of workers between licensed and unlicensed occupations.

To determine the effects of occupational licensing on consumer welfare and labor market outcomes, I set up a static model in which the economy has two productive sectors. In one of the sectors, the good produced is heterogeneous in its quality, an attribute that is unobserved by consumers. In the other sector, a homogeneous good is produced. Workers choose between producing in either sector based on their ability. Licensing policy is modeled as an entry barrier workers face when entering the sector with the information asymmetry, which I refer to as the *licensed sector*. Specifically, workers must incur in an entry fee as well as training. Training is costly in terms of time, the *opportunity cost of licensing*, and in terms of the effort, the *effort training cost of licensing*. The effort training cost is increasing in the amount of training content and decreasing in the ability of workers. Intuitively, workers must exert more effort the greater the training content. Also, given a level of training content, workers of higher ability have to exert less effort in relation to their lower ability counterparts. The training requirements of licensing provide sector-specific skills that augment workers' produc-

tivity in that sector. Workers in the licensed sector produce goods with a quality that is determined by their ability and also by sector-specific skills obtained from training. Consumers obtain utility from consuming quantities of the goods from both sectors and from the quality of the licensed sector good.

In an economy without licensing the standard result of Akerlof (1970) holds: lower quality goods are produced in the sector with the information asymmetry. The reason for this is that the information asymmetry in the product market affects the allocation of workers in the labor market. In the licensed sector, worker's earnings are the same regardless of their ability. This is because the price of licensed goods is the same, as shoppers cannot differentiate the qualities of these goods. As a result, in the licensed sector, high ability workers are undercompensated and low ability workers are overcompensated for their ability. On the contrary, in the unlicensed sector, workers are always fully compensated for their ability as there are no information asymmetries in that sector. Under no licensing requirements, high ability workers enter the unlicensed sector and low ability workers enter the licensed sector.

The training component of licensing plays an important role in alleviating the negative effects of the information asymmetry on the quality of the licensed good. When a licensing policy with training is introduced into the economy, it affects the quality of licensed goods through two channels: the sorting channel and the sector-specific skills channel. Licensing policy determines the composition of ability of workers between the licensed and unlicensed sectors, which I refer to as the *sorting channel*. As training requirements increase, workers of lower ability select out of licensed occupations, since it is more costly for them to carry out the training. Given this, quantity falls which increases the price of licensed goods. As a result, higher ability workers find it more profitable to enter the licensed sector, improving the overall quality of licensed goods. The *sector-specific skills channel* impacts quality directly as workers' quality production is augmented by the skills workers obtain through training. Thus, higher training requirements increase the quality of licensed goods, which raises consumer welfare and increases the wage premium. However, as license costs increase, households must spend more resources on these costs, resulting in lower quantities of both goods being consumed. Hence, higher training requirements reduce the quantities of goods traded, which lowers the welfare of households. In summary, although increasing training requirements of licensing may alleviate the adverse selection problem by improving the quality of licensed goods, it generates a higher deadweight loss through less resources being spent on quantity consumption.

I use the 2008 SIPP panel and the O*NET database to estimate the model. More specifically, I analyze occupations that are similar in the education level of their workers, by focusing on occupations that are predominantly made up of workers with less than college education. I refer to these occupations as low-skilled occupations. In this manner, I am controlling for differences in education that may have a clear impact on occupational choice. For workers in these occupations, I document that only 15 percent of them are licensed and, on average, the wages of licensed workers is 16 percent higher. Next, I decompose this wage premium and find that 9 percentage points are accounted for by skill observables in the data, which I refer to as the skill component.

I estimate the model to moments from my sample of workers in low-skilled occupations. Using the estimated model, I determine how much of the skill component is explained by the sorting channel and how much is explained by the sector-specific skills channel. I find that skills obtained from training play an important role in explaining the 9 percentage point skill component. I also use the estimated model to carry out counterfactual policy analysis. In particular, I compare the current US economy, which I refer to as the benchmark, to alternative economies with different licensing policies. The main counterfactual policy analysis I carry out is to eliminate the training requirements of licensing, while keeping the homogeneous fee constant. I find that under this counterfactual, consumer welfare falls in 3.9 percent and the wage premium falls by more than half. Although consumer welfare improves as more quantities are traded in equilibrium, this is offset by a reduction in the quality of licensed goods. The fall in the quality is driven mainly by the sorting channel. With respect to the wage premium, the drastic fall is driven by a fall in the skill component. Furthermore, the decrease in the skill component is explained in 78 percent by the sorting channel and in 22 percent by the removal of sector-specific skills. I also consider counterfactual licensing policies in which the training requirements vary. I find that an optimal licensing training policy, leads to an increment in consumer welfare of 2.6 percent. Last, I evaluate the case in which training requirements are kept the same as in the benchmark economy and the fee component of licensing is eliminated. Under this counterfactual scenario, welfare only improves in 0.1 percent.

1.2 Related Literature

This chapter contributes to the growing literature on occupational licensing and its effects on the product and labor markets. The traditional argument in favor of a licensing policy is that there exists an information asymmetry between consumers and producers in the markets of goods and services.

In this manner, a licensing policy can improve welfare of consumers if it can raise the quality of goods produced. Leland (1979), Shaked and Sutton (1981a,b, 1982a,b), and Shapiro (1983, 1986) develop models to qualitatively analyze product markets associated with information asymmetries in the quality of goods. Moreover, this earlier literature evaluates the welfare and earnings implications of regulating the producers of these goods. In particular, Shapiro (1986) proposes a model with moral hazard, in which professionals underinvest in the quality of goods they produce. By raising investment requirements, licensing alleviates the information asymmetry and raises the quality of products. Leland (1979) sets up a model, in the spirit of Akerlof (1970), in which there is adverse selection in the product market as quality of goods cannot be observed. Under this market structure, he evaluates the welfare implications of introducing a minimum quality standard for products. Furthermore, Leland (1979) points out that licensing standards chosen by a professional group can lead to other inefficiencies, such as market power of the licensing group.

The theoretical framework I develop in this chapter most closely relates to Leland (1979), as the information asymmetry is adverse selection. The main difference between the previous theoretical work and my framework, is that licensing policy not only has implications for the quality of goods that are produced, but also affects the occupational choice of workers. Shaked and Sutton (1981a,b) evaluate the coexistence of competing professions, but in their analysis workers do not endogenously choose to enter the different professions. In my theoretical framework, workers choose to allocate into different occupations based on ability, the licensing policy, and the effects of the information asymmetry that carries over from the product market to the labor market.

More recent work has tried to determine the quantitative implications of licensing for welfare. An extensive list of articles have analyzed the effects of licensing on the quality of goods produced. The main argument is that if licensing policy raises the quality of goods, then consumer welfare increases. These papers have mainly focused on analyzing the licensing effects on quality for specific occupations and conclusions vary according to each case study.¹ For example, Kleiner and Kudrle (2000) and Wiswall (2007) find that stricter licensing requirements do not improve the quality of dentists and teachers, respectively. On the other hand, Adams III et al. (2003) and Anderson et al. (2016) find opposite results on the quality of services of midwives. Kleiner and Soltas (2018) develop a richer theoretical framework to explain the welfare effects of occupational licensing, without

¹ Papers that have analyzed the effects of licensing on quality are Adams III et al. (2002), Adams III et al. (2003), Anderson et al. (2016), Barrios (2018), Carroll and Gaston (1981), Kleiner and Kudrle (2000), Kleiner and Petree (1988), Kugler and Sauer (2005), Larsen (2013), Wiswall (2007), among others.

modeling a market failure. In particular, they argue that the quantity of labor hours is a sufficient statistic for welfare analysis and find that the welfare costs of licensing offset its benefits.

A caveat of the work highlighted above is that the theoretical framework used for quantitative analysis abstracts from modeling any market failure which can be corrected by occupational licensing. I contribute to this literature by explicitly modeling an information asymmetry in the product market. Incorporating an information problem into the theoretical model is key in exemplifying the role of licensing in the economy and the trade-off it generates. More specifically, the interaction between the information problem and the licensing policy has a direct impact on the quality of goods produced in the licensed sector as well as the allocation of workers between licensed and unlicensed occupations. To my knowledge, I am the first to quantitatively evaluate this trade-off.

Finally, I contribute to the extensive empirical analysis of the effects of licensing on labor market outcomes. The main consensus is that licensing acts as a barrier to entry that restricts the quantity of goods sold in licensed occupations, as highlighted by Blair and Chung (2018a), Friedman (1962), Gittleman et al. (2017), Kleiner (2000), Kleiner and Krueger (2013), Kleiner and Soltas (2018), Thornton and Timmons (2013), among others. Another related topic that has been vastly studied is the wage differential between licensed and unlicensed workers. Work by Blair and Chung (2018b), Kleiner and Krueger (2013, 2010), Kleiner and Soltas (2018), Thornton and Timmons (2013), among others, have estimated a wage premium of licensed workers between 6 and 15 percent, for different data sets. Most studies find that controlling for observables of skills explain some of the wage premium but not all. The remaining difference has been attributed to rents generated by quantity restrictions, Kleiner and Krueger (2013), or by information asymmetries, Blair and Chung (2018b).

By modeling an endogenous occupational choice, I contribute to the literature by providing a selection mechanism of workers into occupations, which depends on the physical environment, the worker's ability, and the licensing policy. Hence, I am able to analyze the effect of licensing on the quantity supply of labor and on the quality (ability) supply of labor into licensed occupations. I also complement the wage premium analysis of the literature by decomposing it into components that are attributed to differences in workers' ability between sectors, training requirements of licensing, and information rents.

1.3 Theoretical Framework

This section provides a description of the theoretical framework. First I describe the physical environment of the model in absence of licensing. I characterize the equilibrium for this case. Then, I extend the model to include licensing policy and characterize the equilibrium for this case.

1.3.1 Environment

I consider a static model with adverse selection in the goods market and occupational choice in the labor market. The economy is populated by a continuum measure 1 of identical households. Each household is composed of one shopper and a continuum of measure 1 of workers. There are two productive sectors, $j = 1, 2$, in the economy. Workers are heterogeneous in their ability, a . Given their ability, workers choose to produce between the two sectors. Within each sector, a worker is self-employed and uses his ability and equipment, m , to produce. Households own all the equipment in the economy and supply it inelastically. In sector 1, the goods produced are differentiated in their quality. A worker in this sector produces goods of a specific quality which depends on his ability. In sector 2, workers produce a homogeneous good. The good produced in sector j will be referred to as good j . The shopper cannot observe the specific quality, x_1 , produced by a worker in sector 1. He randomly chooses a worker and buys quantity c_1 from that self-employed worker. In sector 2, the good's quality is homogeneous and the shopper purchases quantity c_2 in the market. Households have preferences over the quantities of goods produced in each sector and over the quality of good 1.

1.3.2 Workers and Production

Workers are heterogeneous in their ability $a \in [\underline{a}, \bar{a}]$, which is distributed according to $\mu(a)$. A production unit is made up of a single worker with ability a , who acts as an entrepreneur. This worker uses his ability and rents equipment, m , in order to produce. In sector 1, a worker of ability a produces a quantity of goods with technology:

$$f_1(m) = m^\theta, \tag{1}$$

where θ is the output elasticity of equipment. The goods produced by worker of ability a have quality:

$$x_1(a) = a. \quad (2)$$

In sector 2, a worker uses his ability and equipment for quantity production

$$f_2(a, m) = am^\theta. \quad (3)$$

1.3.3 Occupational Choice

A worker of ability a , must choose between producing in sector 1 or sector 2. In sector 1, a worker obtains earnings $w_1(a)$:

$$w_1(a) = \max_m p_1 f_1(m) - rm, \quad (4)$$

where r is the price of equipment. It is important to note that since quality is not observed for the sector 1 good, then there exists only one price for that good, p_1 . Hence, workers in sector 1 are not compensated for the specific quality that they produce with technology (2). This quality is produced at no cost. In sector 2, a worker obtains earnings $w_2(a)$:

$$w_2(a) = \max_m f_2(a, m) - rm. \quad (5)$$

The sector 2 good is the numeraire good of the economy. I denote $m_j(a)$ as the amount of equipment demanded by the production unit with worker of ability a in sector j . Given the quantity production technologies (1) and (3), the share of output of a production unit that corresponds to a worker is $1 - \theta$. Last, a worker's occupational choice is given by:

$$w(a) = \max_{d \in \{1,0\}} d[w_1(a)] + [1 - d]w_2(a). \quad (6)$$

1.3.4 Household Problem

Good 1 is differentiated in its quality level $x_1(a)$, which depends on the ability, a , of the worker that produces it. Ex ante, the household's shopper cannot differentiate the specific quality produced by a worker in sector 1. Due to the information problem, shoppers have beliefs $\sigma(a)$ about the distribution of qualities of good 1, i.e. the different abilities of workers in sector 1. Given his beliefs,

the shopper chooses to buy a quantity c_1 of good 1 and randomly chooses a worker to buy it from. Good 2 is homogeneous and the shopper buys quantity c_2 of this good in a competitive market. Ex post, the household obtains utility $U(c_1, x_1(a), c_2)$ from consuming both goods of the economy.² The sources of income of the household are the earnings of its workers, $w(a)$, and the income from renting equipment.

The household's problem is given by:

$$\begin{aligned} \max_{c_1, c_2} \quad & E_\sigma [U(c_1, x_1(a), c_2)] \\ \text{s.t.} \quad & \end{aligned} \tag{7}$$

$$p_1 c_1 + c_2 = \int_{\underline{a}}^{\bar{a}} w(a) \partial \mu(a) + r \int_{\underline{a}}^{\bar{a}} [d(a) m_1(a) + [1 - d(a)] m_2(a)] \partial \mu(a).$$

Households choose $\{c_1, c_2\}$ to maximize their utility. By assumption, there is perfect consumption insurance within each household. This is because all workers pay out their earnings to be shared equally in the household. The combination of this with the law of large numbers across households, allows for the construction of a representative household.

1.3.5 Characterization of Equilibrium

Since households are identical, they all demand the same quantities of each good. Given that the measures of households and workers are 1, any household's consumption of c_j is equal to aggregate consumption of good j . Likewise, the demand of equipment for a worker of ability a is equal to the aggregate demand of equipment for all workers with that ability. I denote uppercase letters as aggregate quantities. The competitive equilibrium is defined as follows. Given the ability distribution $\mu(a)$, a competitive equilibrium consists of relative price p_1 , workers' occupational choice $d(a)$ and equipment choice $m_j(a)$, households' consumption choices $\{c_1, c_2\}$ and beliefs $\sigma(a)$ such that:

1. Given $\sigma(a)$ and p_1 , $\{c_1, c_2\}$ solve the households' problems.
2. Given p_1 , $d(a)$ and $m_j(a)$ solve the workers' problems.

²A result of Akerlof (1970) is that in certain cases, markets can completely shut down when there exists adverse selection. The intuition of why this happens is as follows. The price, p_1 , determines the quality of goods produced in sector 1. In particular, higher ability workers may not be willing to produce in sector 1, given that they may be underpaid in terms of their ability given a value of p_1 . Without any assumptions on the demand of good 1, it can be the case that all workers are underpaid in sector 1 and decide to produce in sector 2. To avoid this issue, I assume that households always consume positive quantities of both goods:

$$\lim_{c_j \rightarrow 0} \frac{\partial U(c_1, x_1(a), c_2)}{\partial c_j} = \infty.$$

3. Markets clear:

$$C_1 = \int_{\underline{a}}^{\bar{a}} m_1(a)^\theta I_{\{d(a)=1\}} d\mu(a),$$

$$C_2 = \int_{\underline{a}}^{\bar{a}} am_2(a)^\theta I_{\{d(a)=0\}} d\mu(a).$$

4. Beliefs are consistent:

$$E_\sigma[x_1(a)] = \frac{\int_{\underline{a}}^{\bar{a}} am_1(a)^\theta I_{\{d(a)=1\}} d\mu(a)}{\int_{\underline{a}}^{\bar{a}} m_1(a)^\theta I_{\{d(a)=1\}} d\mu(a)}.$$

The consistency condition on beliefs has the following interpretation. In equilibrium, the expected value of quality for households given their beliefs is equal to the average quality of good 1 that is produced. As can be seen from the right hand side of the consistency condition, the average quality in sector 1 is equivalent to the total quality-adjusted output divided by the total output in that sector.

Due to the information structure, the competitive equilibrium defined above is characterized by having workers of low ability in sector 1 and workers of high ability in sector 2. There exists a cut-off ability, $\tilde{a} \in [\underline{a}, \bar{a}]$, such that workers with $a \leq \tilde{a}$ enter sector 1 and workers with $a > \tilde{a}$ enter sector 2. See section A.1 in the Appendix. The proposition above highlights important implications of the adverse selection problem on the goods and the labor markets. The households' demands for both goods as well as the equilibrium conditions determine cut-off \tilde{a} , which defines the allocation of workers between productive sectors. In equilibrium, this cut-off is equal to the equilibrium price, p_1 . Workers below this cutoff are overcompensated by p_1 , since they receive extra rents due to the information problem. On the other hand, workers above the cut-off \tilde{a} are undercompensated by p_1 . For this reason they decide to enter sector 2, where their earnings fully reflect their ability. Hence in equilibrium, sector 1 is characterized by having the least able workers, as predicted by Akerlof (1970).

1.3.6 Licensing Policy

As highlighted in section 1.3.5, due to the information problem, only low ability workers enter sector 1, producing low quality goods. Given households preferences, a policy that increases the quality of good 1 in the market has the potential to improve welfare. Therefore, I analyze the effects of introducing a licensing policy into the economy. I assume there exists a government agency that sets up a licensing policy to alleviate the effects of adverse selection on the quality of goods produced in

sector 1. For the remaining of the chapter, I will also refer to sector 1 and sector 2 of the theoretical model as the licensed and unlicensed sectors, respectively.

Licensing is made up of two components, a fee that a worker must pay to enter sector 1 and a training requirement for all workers. I define the licensing policy as $\Gamma = (F, T, \tau)$, where F is the licensing fee, T is per period equivalent of the required amount of time in training, and τ is the per period equivalent of the required amount of training content³. Workers that wish to enter sector 1 must pay a cost $\psi(a, \Gamma)$, that depends on their ability and the licensing policy Γ . I assume that the license cost is paid in terms of the numeraire good. I explicitly define the cost as:

$$\psi(a, \Gamma) = \underbrace{F}_{Fee} + \underbrace{\psi^o(a, T)}_{\text{Opportunity Cost of Training}} + \underbrace{\psi^e(a, \tau)}_{\text{Effort Cost of Training}}, \quad (8)$$

where ψ^o is the flow value of the opportunity cost of training and ψ^e is the flow value of the effort cost of training.⁴ I make the following assumptions on the opportunity cost of training: $\psi_a^o > 0$ and $\psi_T^o > 0$. This implies that training is costlier the higher the time requirement and the higher the ability of the worker. Further, I assume that the effort cost of training has the following properties: $\psi_a^e < 0$ and $\psi_\tau^e > 0$. Given a level of training content, workers of lower ability must exert more effort in training relative to their higher ability counterparts. Also, as the required training content increases, then the effort cost of training rises.

Although training is costly, it also has benefits as it improves the productivity of workers within sector 1. More specifically, I assume that a worker that acquires training through licensing augments his ability in sector 1 with an exogenous level of skill, $g(\tau)$, which is only useful in the quality production of sector 1. Equation (2) becomes:

$$x_1(a, \tau) = ag(\tau). \quad (9)$$

Hence, $g(\tau)$ captures the sector specific training that workers obtain due to the licensing process.

³Many workers that get a license must earn a certain amount of education or specialized training as well as passing one or multiple exams.

⁴In the US, workers incur in the costs of licensing before they enter the licensed occupation. Given that I have a static framework, I assume that the cost of licensing is paid once as a flow value. For simplicity, I measure the effort cost of training in terms of resources.

1.3.7 Characterization of Equilibrium with Licensing Policy

In an economy with licensing, workers that enter the licensed occupation must pay $\psi(a, \Gamma)$. As a result, earnings in sector 1 are:

$$w_1(a) = \max_m p_1 f_1(m) - rm - \psi(a, \Gamma). \quad (10)$$

Earnings in sector 2 are given by (5), and a worker of ability a solves the problem defined by (6). I denote $\Psi(a, \Gamma)$ as the aggregate license cost of workers of type a . I assume that the aggregate license cost in the economy, $\int_{\underline{a}}^{\bar{a}} \Psi(a, \Gamma) I_{\{d(a)=1\}} d\mu(a)$, is not rebated back to the households. In an economy characterized by licensing, the competitive equilibrium is given by the following definition. Given the ability distribution $\mu(a)$ and licensing policy Γ , a competitive equilibrium of the economy with licensing consists of relative price p_1 , workers' occupational choice $d(a)$ and equipment choice $m_j(a)$, households' consumption choices $\{c_1, c_2\}$ and beliefs $\sigma(a)$ such that:

1. Given $\sigma(a)$ and p_1 , $\{c_1, c_2\}$ solve the households' problems.
2. Given p_1 and Γ , $d(a)$ and $m_j(a)$ solve the workers' problems.
3. Markets clear:

$$C_1 = \int_{\underline{a}}^{\bar{a}} m_1(a)^\theta I_{\{d(a)=1\}} d\mu(a),$$

$$C_2 + \int_{\underline{a}}^{\bar{a}} \Psi(a, \Gamma) I_{\{d(a)=1\}} d\mu(a) = \int_{\underline{a}}^{\bar{a}} a m_2(a)^\theta I_{\{d(a)=0\}} d\mu(a).$$

4. Beliefs are consistent:

$$E_\sigma[x_1(a, \tau)] = \frac{\int_{\underline{a}}^{\bar{a}} a g(\tau) m_1(a)^\theta I_{\{d(a)=1\}} d\mu(a)}{\int_{\underline{a}}^{\bar{a}} m_1(a)^\theta I_{\{d(a)=1\}} d\mu(a)}.$$

1.4 Data and Calibration

The model is calibrated to match features of the labor market for occupations comprised of workers with low education levels. I refer to these occupations as low-skilled occupations. By focusing on these occupations, I use the theoretical model developed in section 1.3 to study product markets associated with workers of similar skill levels. In this manner, I control for the effect that educational

attainment can have on occupational choice.⁵ I use data from the Survey of Income and Program Participation (SIPP) 2008 panel and from the O*NET 23.0 Database to construct the sample of workers in low-skilled occupations. Below, I first describe the construction of my sample, and then I explain the estimation of my theoretical model.

1.4.1 Data

I use three data sources to define the calibration target moments. The first data set I use is the 2008 panel of the Survey of Income and Program Participation (SIPP). This panel is a nationally representative data set, which was carried out in 16 quarterly waves covering the period between September 2008 and December 2013. The data set has information on wages, employment and occupations for a large number of individuals. Each wave has a corresponding topical module. I link the core data from wave 13 of the SIPP with the data of its corresponding topical module, the Professional Certifications, Licenses, and Educational Certificates module. This specific wave corresponds to the period between May and November of 2012 and has been used in two empirical pioneer studies of the occupational licensing literature, Blair and Chung (2018b) and Gittleman et al. (2017).⁶ Using two specific questions from this topical module, I define a worker as licensed in the same manner as Gittleman et al. (2017). That is, I classify a worker as licensed if he possesses a professional credential and if this credential was awarded by a federal, state, or local government.⁷

I follow the criterion of Gittleman et al. (2017) when constructing my sample. I focus on individuals with ages between 18 and 64 years that are in the civilian labor force. Using data on monthly earnings, weeks worked, and weekly hours worked, I construct hourly wages and include in the sample only respondents with hourly wages between \$5 and \$100. The SIPP collects information on up to two jobs or up to two businesses for each worker, but does not clarify which of these jobs or businesses is the relevant one for the credential of the worker. I assume that the credential is relevant to the job or business for which the worker has the highest wage. Last, I exclude from the sample workers with imputed data for wages and worker's who did not provide a response for the credential relevant questions.^{8 9}

⁵Hence, I exclude unreasonable comparisons such as an individual choosing between working as a medical doctor, a highly educated licensed occupation, and a waitress, a low educated unlicensed occupation.

⁶Gittleman et al. (2017) explain with strong arguments the advantages of using the SIPP data set.

⁷The two questions that allows me to identify a worker as licensed are: 1) "Do/Does you/he/she have a professional certification or state or industry license?" and 2) "Who awarded this certification or license?"

⁸Including imputed wages in the estimation of the wage premium and the skill component in section 1.4.2 would bias estimates of these premiums towards 0 as explained by Hirsch and Schumacher (2004).

⁹The non-response rate of workers for questions about credential status is 3.3 percent.

To determine whether an occupation is low or high skilled I use the O*NET 23.0 Database. This database describes 968 occupations using 277 descriptors. These descriptors are classified into 9 broad categories.¹⁰ Information for each descriptor is gathered from either a survey of workers or from a survey “occupational analysts”. Respondents of the worker survey are asked to report the required level of education for their occupation. I classify an occupation as low-skilled if “less than college” is the most common required level of education for the survey respondents of that occupation, and as high-skilled if “at least college” is the most common response. I link this classification of occupations by education to the panel of workers of wave 13 of the SIPP.¹¹ Out of the 460 occupations in the SIPP, 325 are low-skilled occupations. These account for 68 percent of all workers.

For my sample of workers in low-skilled occupations, the average monthly earnings is \$3,986. Table 1 presents a set of descriptive statistics for the observations in my sample, separately for licensed and unlicensed workers. On average, licensed workers have higher wages, are older, and are more educated, relative to their unlicensed counterparts. Also, licensed workers have a higher participation of women and have a higher number of workers in the government, in a service industry, and in unions. These patterns are consistent to those found by Blair and Chung (2018b) and Gittleman et al. (2017).

¹⁰The categories are: Knowledge, Skills and Abilities; Education, Experience, and Training; Interests, Work Values, Work Styles; Tasks; Tools & Technology; Work Activities; Work Context; Related Occupations; Green Occupations.

¹¹Occupations in the O*NET are classified according to the Standard Occupational Classification - SOC. On the other hand, occupations in the SIPP 2008 are classified with the 2002 Census Code Classification. Using a crosswalk between these two different occupation code systems, I am able to link my classification of occupations by education to the worker data of the SIPP panel.

Table 1: Descriptive Statistics - Licensed vs. Unlicensed Workers

	Licensed	Unlicensed
Number of Observations	8,696	47,831
Average Monthly Wage	4,523	3,886
Average Age	42.8	41.0
Share:		
Men	0.49	0.53
Government Workers	0.22	0.11
Services	0.82	0.74
Less than College	0.76	0.83
Union	0.18	0.11

Source: Wave 13 of the SIPP Panel 2008.
Number of observations: 56,527

Note: This table reports summary statistics by licensing status using data from wave 13 of the SIPP Panel 2008. I restrict the sample to workers with age between 18 and 64 and with hourly wage from \$5 to \$100. Observations with imputed wages are dropped.

Carpenter et al. (2012) carry out an in depth analysis of licensing burdens and costs for 102 occupations. They choose occupations that earn less than the national average of income and are at least licensed in one state. For each of these occupations they gather information on the different measures of licensing burdens. In particular, they gather information on different burdens of licensing like fees, amount of time spent on training prior to obtaining a license, number of exams, and minimum age requirements. As explained in section A.2.1 of the appendix, I back out the fee and opportunity cost component of the license cost specified in equation (8) using both my sample of the SIPP and the database of Carpenter et al. (2012). On average, licensed workers in low-skilled occupations pay a fee of \$91 and train for 9 months before they enter a licensed occupation.

1.4.2 Wage Premium Decomposition

The empirical literature on occupational licensing has focused a great deal in understanding the differences in wages between licensed and unlicensed occupations. Studies such as Blair and Chung (2018b), Kleiner (2000), Kleiner and Krueger (2013, 2010), Kleiner and Soltas (2018), among others have documented a wage premium for licensed workers, even after controlling for skill observables.

They explain these differences as coming from monopoly or information rents. I document that for low-skilled occupations the average wage of licensed workers is 16 percent higher than the average wage of their unlicensed counter parts. Similar to Kleiner (2000), I decompose this wage difference using a Oaxaca-Blinder decomposition. Specifically, I regress monthly wages, $w_{i,j}$ on skill observables, $x_{i,j}$ separately for licensed, $j = L$, and unlicensed, $j = NL$, workers:

$$w_{i,j} = x_{i,j}'\beta_j + u_{i,j}. \quad (11)$$

The skill observables which I control for are gender, education, age, and indicators for union membership, government workers, and service workers. I decompose the average wage premium into a skill component and a residual component. The skill component accounts for differences in skills between licensed and unlicensed workers that are accounted for by the skill observables. Hence, this component is explained by differences in the general ability of workers and by the specific skills that licensed workers acquire through the training requirements of licensing. On the other hand, the residual component accounts for monopoly rents, information rents, and any unobservable skill differences between licensed and unlicensed workers:

$$\bar{w}_L - \bar{w}_{NL} = \underbrace{(\bar{x}_L' - \bar{x}_{NL}')\beta_L}_{\text{Skill Component}} + \underbrace{\bar{x}_{NL}'(\beta_L - \beta_{NL})}_{\text{Residual Component}}. \quad (12)$$

Table 2 presents the average wage decomposition results. Of the 16 percent difference in average wages between licensed and unlicensed workers, 9 percentage points are explained by differences in skill observables between licensed workers and unlicensed workers.

Table 2: Wage Premium Decomposition

Wage Premium	0.164 (0.007)
Skill Component	0.090 (0.003)
Residual	0.074 (0.003)

Source: Wave 13 of the SIPP Panel 2008.

Number of observations: 56,527

Estimates are significant at the 1% confidence level. Standard errors in parentheses.

Note: This table reports the Oaxaca-Blinder decomposition of the average wage premium between licensed and unlicensed workers. The unit of observation is person-month. The dependent variable is monthly wage. The human capital regressors are gender, education, age, and indicators for union membership, government workers, and service workers. I restrict the sample to workers with age between 18 to 64 and with hourly wage from \$5 to \$100. Observations with imputed wages are dropped. Wages are normalized by the mean wage of unlicensed workers.

1.4.3 Functional Forms and Assigned Parameters

To calibrate the model, I first specify the ability distribution of workers as a non-standard beta distribution, $\text{betacdf}\left(\frac{a-\underline{a}}{\bar{a}-\underline{a}}; \alpha_a, \beta_a\right)$, with shape parameters α_a and β_a . The advantage of the beta distribution is that it has a bounded support as well as being flexible in the shapes it can take, regardless of only depending on two parameters. Next, I choose functional forms for households' utility $U(c_1, x_1(a, \tau), c_2)$, the ability augmenting training technology $g(\tau)$, and the license cost $\psi(a, \Gamma)$. I assume that the utility function is of the following form:

$$U(c_1, x_1(a, \tau), c_2) = \rho \times x_1(a, \tau) \times \log(c_1) + \log(c_2). \quad (13)$$

By assuming a functional form linear in $x_1(a)$, I nest Leland (1979)'s analysis, such that the expected utility in the households' problem 7 is given by:¹²

$$E_\sigma[U(c_1, x_1(a), c_2)] = \rho \times E_\sigma[x_1(a, \tau)] \times \log(c_1) + \log(c_2). \quad (14)$$

¹²Similar to Leland (1979), the quantity demanded of good 1 satisfies the following properties under this utility specification:

$$\frac{\partial c_1^*}{\partial p_1} < 0, \quad \frac{\partial c_1^*}{\partial E_\sigma[x_1(a, \tau)]} > 0.$$

Hence, household's expected utility Parameter ρ determines how important sector 1 good is for the household. I define the ability augmenting training technology for quality production as:

$$g(\tau) = \max\{\tau^\nu, 1\}. \quad (15)$$

This functional form implies that the quality produced by a worker in a licensed occupation cannot be lower than his ability a , as can be see from (2). Thus, training cannot lower a worker's ability. I define the opportunity cost of licensing and the effort training cost licensing as:

$$\psi^o(a, T) = w_2(a)T, \quad (16)$$

$$\psi^e(a, \tau) = \tau \left(\frac{\bar{a} - a}{\bar{a}} \right)^\gamma. \quad (17)$$

The opportunity cost is the product of a worker's wage in sector 2, the unlicensed sector, and the per period equivalent of the training time requirement. The effort training cost is decreasing in ability, a , and increasing in the per period equivalent of the training content requirement, τ . Parameter γ governs how much more effort a worker of ability a must exert in training relative to the highest ability worker, \bar{a} .

The list of assigned parameters are given in Table 3. I set r , the price of equipment, so that it implies a period discount rate of 0.996.¹³ Hence the price of renting equipment is equal to 0.003. I set the output elasticity of equipment, θ , to match the average of the labor income share between 2010 and 2016 for the United States. Using my sample from the SIPP and the database provided by Carpenter et al. (2012), I calculate the per period equivalent of the license fee, F , and the per period equivalent of the training time requirement, T . This is explained in further detail in section A.2.1 of the appendix.

¹³This discount rate is used to calculate the flow values of the license cost components, as explained in section A.2.1 of the appendix.

Table 3: Assigned Parameters

Parameter	Value	Description	Source
r	0.003	Price of Equipment	Implies discount rate of 0.996
$1 - \theta$	0.54	Labor income share	BEA 2010-2016
T	0.04	Training time requirement	SIPP, Carpenter et al. (2012)
F	3.94	License fee	SIPP, Carpenter et al. (2012)

r is monthly real interest rate. F is the per period equivalent of the present discounted value of total licensing fees and T is the per period equivalent of the training time requirement.

1.4.4 Internally Calibrated Parameters

I calibrate the parameters associated with the ability distribution, the utility function, and training to match wages and employment moments from my sample. I report the parameter values from the calibration in Table 4. Although parameters are jointly calibrated, there are some data moments that are more informative about specific parameters. The ability distribution parameters, α_a and β_a are pinned down primarily by the mean and standard deviation of wages from my sample. The parameter ρ controls the weight that the sector 1 good has in the utility function. Hence, ρ determines the quantity demanded of good 1. In equilibrium, the quantity demanded of good 1 is directly related to the amount of workers that supply that good. For this reason, this parameter is primarily pinned down by the share of licensed workers.

The effort training cost, (17), acts as an heterogeneous barrier to entry of workers into licensed occupations. Both τ , the training content requirement, and γ , the parameter that governs the relative effort exerted in training by a worker, shape the severity of the heterogeneous barrier to entry. In the model, there is a direct implication that changes in the severity of the effort training cost of licensing yields changes in the composition of ability between licensed and unlicensed sectors. Furthermore, changes in the ability composition result in changes in the wage premium and in the share of household income that corresponds to licensed workers. Hence these parameters are primarily pinned down to match the 16 percent wage premium between licensed and unlicensed workers and the income share of licensed workers of 18 percent.

Table 4: Internally Calibrated Parameters

Parameter	Value	Target Moments	Model	Data
Distribution:				
α_a	1.06	Mean - wages	3,986	3,986
β_a	2.71	St. Dev. - wages	2,194	2,194
Utility:				
ρ	0.24	Share of lic. workers	0.154	0.154
Training:				
τ	888	Wage premium	1.164	1.164
γ	7.54	Income share of lic. workers	0.175	0.175
ν	0.02	Skill component	1.090	1.090

Training also provides benefits for licensed workers. As can be seen from equations (2) and (15), the quality a worker produces is determined by his ability a and sectors-specific skills $g(\tau)$. Parameter ν determines the amount of sector-specific skills that licensed workers obtain from the training content requirement, τ . In section 1.4.2, I decompose the wage premium of licensed workers into differences in skills between sectors, the skill component, and a residual component. In the model, differences in skill between sectors is determined by the composition of ability between these and by the sector-specific skills obtained through training. Given this, parameter ν is mainly pinned down by the skill component of the wage premium decomposition.

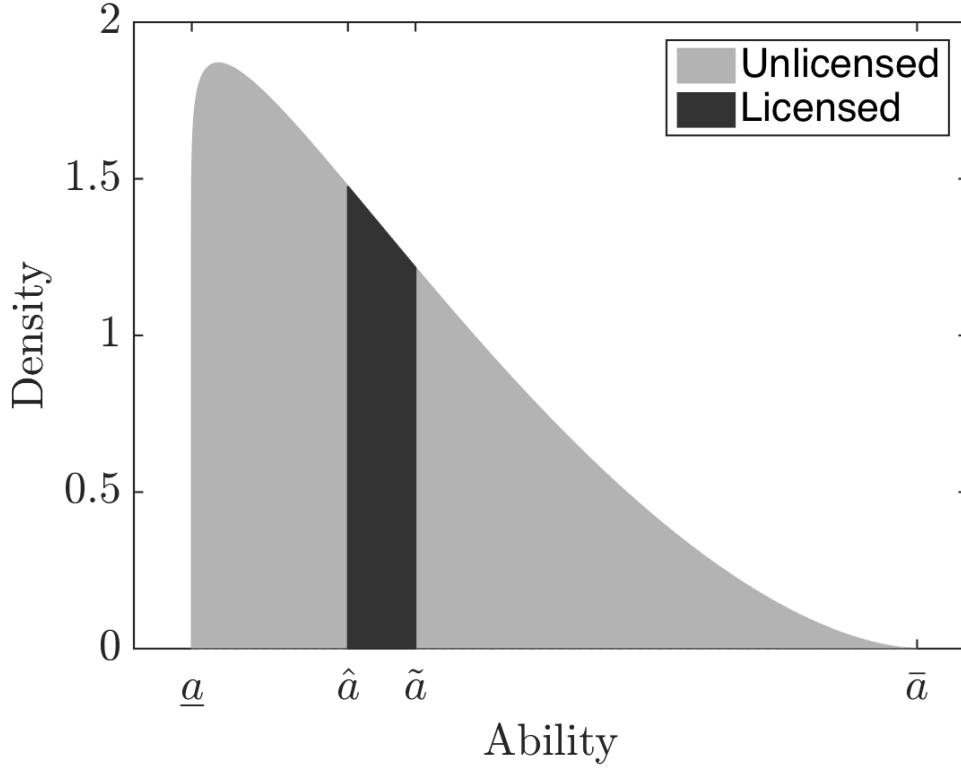
1.5 Licensing Policy in the US

As I explained in section 1.4, I set parameters of my model to match labor market moments of low-skilled occupations. Using this calibration, I am able to characterize the allocation of workers between licensed and unlicensed occupations for the United States. Figure 1 portrays the distribution of ability for my model calibration. Workers with ability $a \in [\hat{a}, \tilde{a}]$ are allocated in the licensed sector, ability interval that accounts for 15 percent of all workers. Workers below ability \hat{a} are those

for which obtaining the license is too costly. Hence, the licensing policy excludes workers of very low ability from entering the licensed sector, as licensing is more costly for them in terms of effort. On the other hand, workers with ability above \tilde{a} enter the unlicensed sector. The reason for this is that, in the licensed sector, the earnings of these workers do not fully compensate them for their high ability. Thus, they choose to enter the unlicensed sector where their earnings fully reflect their productivity.

The current licensing policy ameliorates the effects of the information asymmetry on the quality of licensed sector goods, in comparison to a no licensing policy. It does this through two channels. First, licensing policy has effects on the quality of licensed goods by affecting how workers sort between the licensed and unlicensed sectors given their ability, a , and the license cost. In other words, licensing policy determines the composition of ability a between both sectors. This is the sorting channel I introduced earlier. As can be seen in Figure 1, the current US licensing policy improves the quality of licensed goods in the market by excluding the low ability workers from entering the licensed sector and by incentivizing higher ability workers to enter that sector. Of the workers in the licensed sector, only 27 percent have ability that is higher than the average ability of all workers. Second, quality also improves due to the specific skills obtained through the content of training, which augments ability of workers in the licensed sector in 13 percent. I refer to this channel as the sector-specific skills channel.

Figure 1: Distribution of Ability and Allocation of Workers - Current Licensing Policy



In my calibration strategy, I match the skill component between the licensed and unlicensed sector, which I estimate in section 1.4.2. Using my model, I decompose how much of the skill component is explained by the sorting channel and how much is explained by the sector-specific skills channel. For the sorting channel, the average ability of workers in the licensed sector is 15 percent lower than the average ability of unlicensed workers. With respect to the sector-specific skills channel, training improves the productivity of workers in the licensed sector by 24 percent. The sum of these two components gives the 9 percentage point difference in skills between licensed and unlicensed workers.

Licensing policy also generates a dead weight loss for the economy as households have to spend a portion of their income in license costs. Given the current licensing policy, licensed workers spend 25 percent of their gross earnings on license costs. Of the total license costs in the economy, the effort cost of training accounts for 88 percent, the opportunity cost of training training for accounts for 11 percent, and license fees only account for 1 percent. Hence, the training components of licensing

are the entry barriers which account for most of the deadweight loss of licensing. Given that license costs are paid in units of good 2, I find that they account for 2.8 percent of the output of this good.

1.6 Counterfactual Policy Analysis

In this section, I evaluate the effects of changing the current licensing policy on welfare, the allocation of labor, and the wage premium. First, I explain the measure of welfare I use. Then, I study different counterfactual licensing policies in which I vary training requirements as well as license fees.

1.6.1 Welfare Measure

To study the effects of different licensing policies on welfare I consider the following welfare measure. I define the current licensing policy in the US as Γ^B . I compare all the counterfactual results to this benchmark. Let Γ^N be any counterfactual licensing policy. I measure the difference in welfare between the two economies using a consumption equivalent transfer, ω , in terms of the unlicensed good:

$$\rho \times E_{\sigma} [x_1(a, \tau)]^B \times \log(c_1^B) + \log(c_2^B(1 + \omega)) = \rho \times E_{\sigma} [x_1(a, \tau)]^N \times \log(c_1^N) + \log(c_2^N).$$

The interpretation of ω is the following. Consider two economies, one under the benchmark policy, Γ^B , and another under the new licensing policy, Γ^N . Welfare between the two economies would be equal if the households' consumption of the unlicensed good changed in $\omega \times 100$ percent for the current US economy under the benchmark licensing policy, Γ^B . In the model, the license cost is paid in terms of the numeraire good, which is the unlicensed good. For this reason, I choose the consumption equivalent to be in terms of this good.

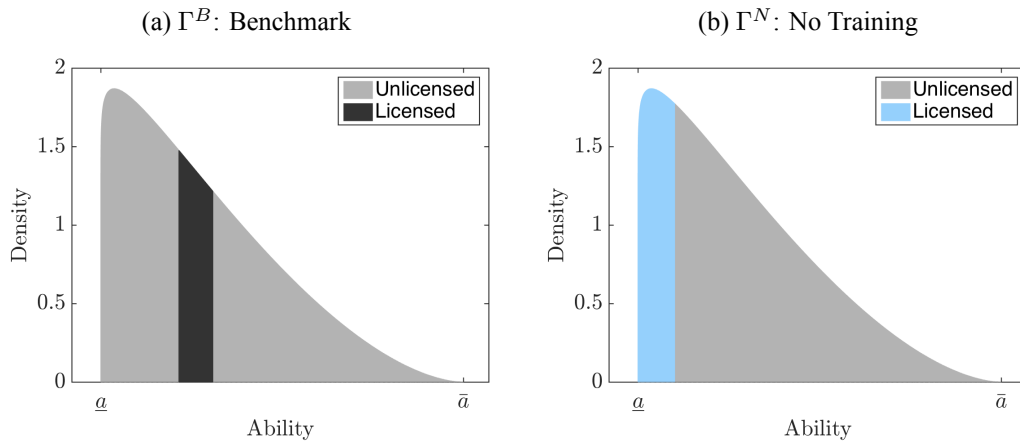
1.6.2 No Training

In this section, I evaluate the effects of eliminating training from the licensing requirements. That is, I set the training time requirement to $T = 0$ and the training content requirement to $\tau = 0$, while keeping the license fee, F , at its calibrated value. Figure 2 shows the ability allocation of workers for the benchmark policy and for the no training counterfactual policy. A change in the licensing policy generates a change in the composition of ability between the licensed and the unlicensed sector. In

particular, a no training policy shuts off the heterogeneous portion of the license cost in (8). By eliminating the effort training cost, lower ability workers become licensed since they only have to pay a small licensing fee instead of paying the large training cost associated with their ability type in the benchmark licensing policy. As a result, the relative price falls since the supply of the licensed good increases as more workers enter this sector. Given this, higher ability workers are not fully compensated anymore in the licensed sector, and decide to produce in the unlicensed sector.

By eliminating training, quality is affected through both the sorting channel and the sector-specific skills channel. The sorting channel is clearly depicted in Figure 2. By eliminating the effort training cost, low ability workers are no longer excluded from the licensed sector. Also, a lower equilibrium relative price incentivizes higher ability workers to exit the licensed sector. This change in the composition of ability between both sectors results in lower quality goods being produced, since the licensed sector is now comprised of lower ability workers. When training is eliminated, the sector-specific skills channel is shut-off so that $g(\tau) = 1$. Thus, quality also falls since ability is not augmented by training anymore. It is important to note that the license fee by itself is not able to generate the sorting effect seen in Figure 2. This is because the fee is small and also because it affects all workers homogeneously. Hence, as it cannot exclude low ability workers from entering the licensed sector, then it is not able to alleviate the negative effect of the information asymmetry on the quality of the licensed good.

Figure 2: Distribution of Ability and Allocation of Workers - Benchmark vs. No Training



Moving from the benchmark policy to a counterfactual policy leads to a change in welfare that

is due to changes in the average quality of the licensed good, $E_{\sigma} [x_1 (a, \tau)]$ and in the consumption quantities of both goods, $\{c_1, c_2\}$. As shown in Table 5, if the US was to implement a no training counterfactual policy, then consumer welfare would fall in 3.9 percent. When moving from the benchmark to the no training policy, the sorting channel and the sector-specific skills channel are eliminated. This results in a reduction in average quality that implies a 11.1 percent drop in welfare. On the other hand, the quantities consumed of both goods increase. For the licensed sector good, c_1 increases since there is a larger number of workers producing in the licensed sector, as can be seen in the first column of Table 6. Although there is a larger number of units consumed of the licensed good, the fall in welfare that comes from the reduction in quality is only offset by 0.1%. On the contrary, consumer welfare improves by 7.1 percent through a higher consumption of good 2. In equilibrium there is a higher quantity of good 2 because both demand and supply is higher for that good. Since quality falls the relative weight of good 2 in the expected utility (14) increases, which implies a higher demand for that good relative to the benchmark policy. Supply for that good increases since higher ability workers are now allocated in sector 2, which implies that output is larger. Overall, I find that eliminating training requirements from the licensing policy has a negative impact on the economy. Although welfare increases since more resources are now allocated towards quantity consumption, removing training requirements is also costly since lower quality licensed goods are produced. The latter effect is stronger than the former, resulting in the overall fall in consumer welfare.

Table 5: Decomposition of Change in Welfare - No Training (%)

Δ Welfare	Quality of $j = 1$	Quantity of $j = 1$	Quantity of $j = 2$
-3.9	-11.1	0.1	7.1

There are large effects on the labor market from eliminating training from the licensing policy as can be observed from Table 6 and Table 7. There is an increase in 7 percentage points in the share of licensed workers. Since lower ability workers allocate into the licensed sector, average ability of that sector falls in 38 percent. Furthermore, licensed workers' average productivity falls even more, in 51 percent, since sector-specific skills have been eliminated. On the other hand, as workers of higher ability enter sector 2, the average ability of its workers improves which implies a higher production

of sector 2 goods.

Table 6: Change in Labor Allocation - No Training (%)

Share of Workers $j = 1$	Average Ability in $j = 1$	Average Ability in $j = 2$
37.9	-38.3	8.8

The fall in the wage premium is large, when moving from the benchmark policy to the no training policy. Under this counterfactual policy, workers in the unlicensed sector are paid more than twice as much as their licensed counterparts. The fall in the wage premium is mainly driven by a considerable drop in the skill component. Furthermore, 78 percent of the reduction in the skill component is accounted for by the sorting channel and the other 22 percent corresponds to sector-specific skills channel. The effect of the fall of the skill component on the wage premium is offset by an increase in information rents of 12.9 percent, which is explained by the fact that lower ability workers are overcompensated more in the absence of training.

Table 7: Decomposition of Change in Wage Premium - No Training (%)

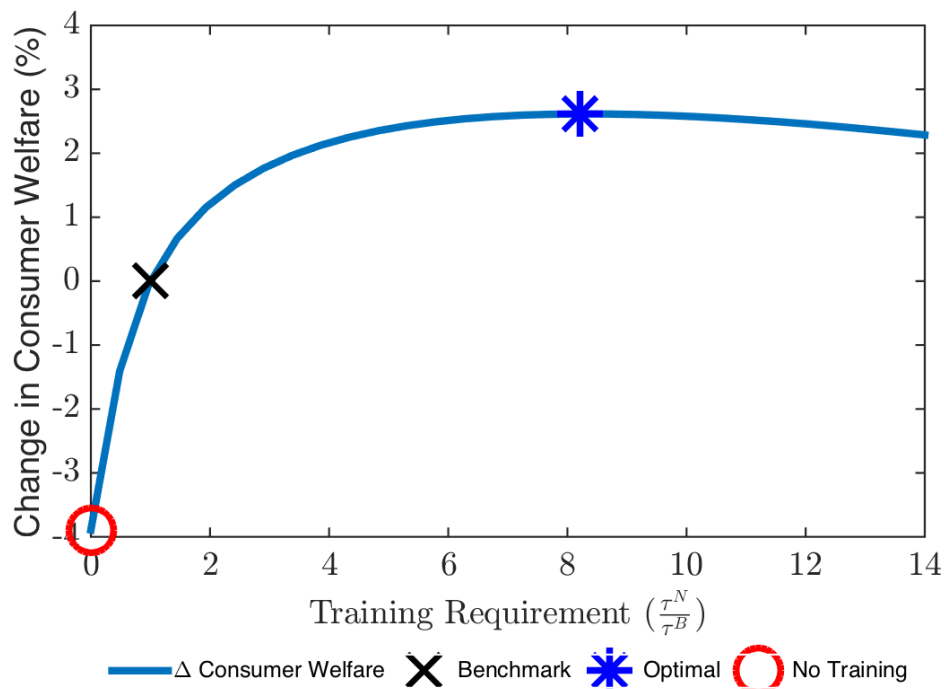
Δ Wage Premium	Δ Skill Component	Δ Information Rents
-94.9	-107.8	12.9

1.6.3 Different Levels of Training Content

In this section, I consider different counterfactual licensing policies that vary on the training requirement (τ^N, T^N) while keeping the license fee fixed at its calibrated value. In particular, a policy that doubles the training requirement means that both the training content, τ^N , and time, T^N , requirements are doubled with respect to the benchmark policy, (τ^B, T^B) . Figure 3 portrays the percent

change in consumer welfare for different levels of training requirements relative to the benchmark licensing policy. I find that the optimal training policy is to increase training requirements by a factor of eight. This number is relatively big, but this is a result of two assumptions I have made on the opportunity cost and license fees when carrying out the quantitative analysis.

Figure 3: Effect of Training Requirements on Consumer Welfare



First, as explained in section A.2.1 of the appendix, I assume that workers only train once throughout their lifetimes. In doing so, I am taking a conservative stance on the calibration of the opportunity cost of training. Many licensing boards require workers to carry-out continuous training in order for them to renew their license. Hence, the value of T^B in my calibration exercise is lower than what it should be. I have made this assumption given that there is no reliable data on the amount of time workers have to spend on training in order to renew their license. Second, also as explained in section A.2.1, when I calculate the per period equivalent of license fees and training time requirements, I assume that workers on average spend 40 years working. By assuming this, the per period equivalents

of license fees and the opportunity cost of licensing are small throughout my quantitative analysis.

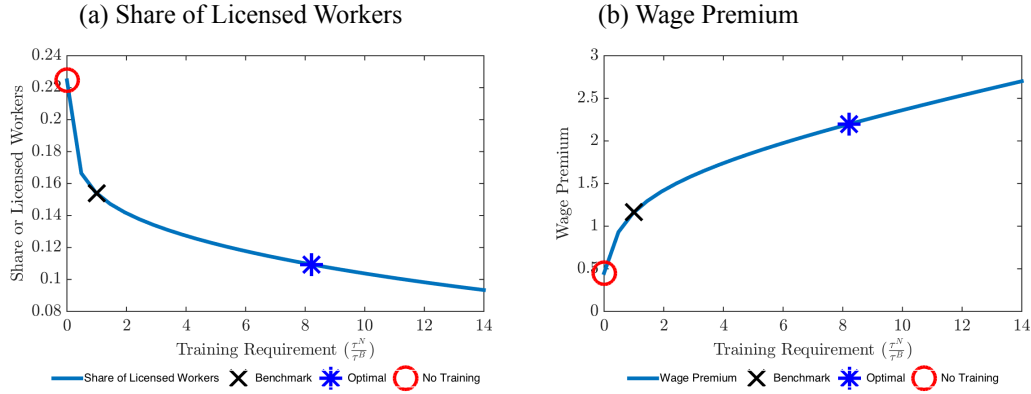
Table 8: Decomposition of Change in Welfare - Optimal Training (%)

Δ Welfare	Quality of $j = 1$	Quantity of $j = 1$	Quantity of $j = 2$
2.6	7.9	-1.7	-3.6

If the US was to move to the optimal training requirement, then consumer welfare would increase in 2.6 percent as seen in Table 8. The mechanics behind this welfare change is similar to the no training counterfactual policy analysis. Quality improves due to the sorting channel and the sector-specific skills channel. With respect to the sorting channel, as the effort training cost becomes higher relative to the benchmark, it becomes even costlier for lower ability workers to pay the license cost. As a result, less workers enter the licensed sector which leads to a reduction in the supply of licensed goods and a higher relative price. The increment in the price incentivizes higher ability workers to enter the licensed sector. As can be seen in Figure 27 of the appendix, higher ability workers enter the licensed sector under the optimal licensing policy in comparison to the benchmark. The effect of the sector-specific skills channel on quality is straight forward. Since workers receive higher content requirements, then they produce higher quality goods. This increase in the quality raises welfare by 7.9 percent. The positive effect on welfare from raising quality is offset by a reduction in the consumption of quantities of both goods. By raising training requirements to the optimal level, household's have to spend more resources on license costs. Given this, they consume less of both goods and welfare is reduced by 5.3 percent.

Figure 4 portrays the effects of different training policies on the labor market. Panel (a) of Figure 4 shows that as training requirements become higher, less workers enter the licensed sector resulting a drop in the share of licensed workers. As training requirements become higher, it is costlier for lower ability workers to enter the licensed sector and it is more profitable for higher ability workers to become licensed. Since higher ability workers have a lower density then the number of licensed workers reduces as license training requirements rise. Panel (b) of Figure 4, shows that as training requirements rise the wage premium also rises. This result is driven by the fact that higher training requirements increase the skill component of the wage premium.

Figure 4: Effect of Training Requirements on the Labor Market



Moving to the optimal training policy implies a reduction of 4.4 percentage points in the share of licensed workers. Tables 18 and 19 in the appendix show the effects on the labor market of moving to the optimal licensing policy. Average ability in the licensed sector increases in 22.7 percent while average ability of unlicensed workers falls by 3.2 percent. Also, under the optimal training policy, the wage premium increases in 63.5 percent relative to the benchmark, mainly driven by a 55.9 increase in the skill component. The increase in the skill component is driven in 86 percent by the sorting channel and in 14 percent by sector-specific skills channel.

1.6.4 No License Fee

In this section, I evaluate the effects of eliminating the license fee, while keeping the training requirements at the same level as in the benchmark licensing policy. As stated in section 1.5, license fees only account for 1 percent of total license costs. For this reason, a licensing policy that only removes license fees generates little effect on the economy. Table 9 shows that eliminating license fees only yields a 0.1 percent increase in welfare relative to the benchmark economy. This change in welfare is driven by a higher quantity of licensed goods being consumed, as eliminating fees implies that more workers enter licensed occupations. However, since fees are small, then only very few workers switch from the unlicensed to the licensed sector. The ability composition of workers remains very similar to the benchmark economy as can be seen in Figure 28 in the appendix. This shows that changes in license fees are less important for the sorting channel in comparison to changes in training requirements. This is because license fees affect all workers homogeneously, while training

affects workers differently depending on their ability. As a result, the heterogeneous training costs have larger effects on the composition of abilities between sectors. For this reason, eliminating only license fees has very little effect on the labor market, as can be seen in Tables 20 and 21 of the appendix.

Table 9: Decomposition of Change in Welfare - No Fee (%)

Δ Welfare	Quality of $j = 1$	Quantity of $j = 1$	Quantity of $j = 2$
0.1	0.0	0.1	0.0

1.7 Conclusion

The objective of this chapter is to evaluate the effects of occupational licensing on welfare and labor market outcomes. To do this, I set up a theoretical framework with information asymmetries in the product market and occupational choice in the labor market. Workers choose occupations based on their ability and the licensing policy. By explicitly modeling the information asymmetry, there is a potential welfare improving role for licensing in the economy. Licensing is modeled as an entry fee and as costly training. I calibrate the model to match specific moments of the US using the 2008 SIPP panel and the O*NET database. I control for differences in education, by calibrating the model to only occupations composed mainly of workers with less than college education. Using the calibrated model, I carry out counterfactual licensing policy analysis. I find that implementing a no training policy leads to a welfare loss of 3.9 percent. Also, the wage premium drops by more than half. I find that these results are driven by changes in the composition of ability of workers between the licensed and unlicensed sector, which I refer to as the sorting channel.

2 Corporate Tax Rates, Allocative Efficiency, and Aggregate Productivity

2.1 Introduction

Corporate tax regulation generates heterogeneity in the effective tax rates faced by firms due to exemptions, deductions, and deferrals. At the same time, there is a large amount of dispersion in firm-level productivity even within narrowly defined industries. As a result, effective corporate tax rates can potentially generate an inefficient allocation of resources across firms, which directly affects total factor productivity (TFP).

This chapter quantifies the effect of effective corporate tax rates on aggregate TFP through allocative efficiency. First, we use Chilean manufacturing census data for the years 1998 to 2007 and document several characteristics of the effective tax rate distribution. Two important findings are a large dispersion in the effective tax rate faced by firms and a mass of firms with a 0 percent tax rate. Next, we incorporate these features into a standard monopolistic competition model with capital and output wedges, where firms endogenously choose the tax rate they face. We then calibrate the model and find that if there were no corporate taxes in the economy, TFP would increase between 4 and 11 percent. Afterward, we study the effects of imposing the same tax rate on all firms, which we call a flat tax rate policy. We find a monotonically decreasing relationship between the level of the flat tax rate and TFP.

This chapter contributes mostly to the misallocation literature pioneered by Hsieh and Klenow (2009) and Restuccia and Rogerson (2008). This stream of literature documents large differences in TFP through the resource allocation channel. Following the categorization proposed in the survey by Restuccia and Rogerson (2017), the literature has studied misallocation via two approaches. The direct approach selects a factor that can potentially cause misallocation and measures its effects on allocative efficiency and TFP. Examples of such factors are financial frictions, firing costs, and size-dependent policies. The indirect approach tries to measure the net effect of all the possible factors that generate misallocation without specifying a definite source. One caveat with this approach is that any misspecification of the theoretical model used to measure misallocation can potentially overstate it. We combine these two approaches by identifying a specific factor of misallocation, effective corporate tax rates, while also accounting for all other possible latent factors that could generate misallocation or model misspecification. By taking this approach, we are able to study

the effect of heterogeneous effective corporate tax rates while accounting for any other distortion or model misspecification.

To carry out our analysis, we use the ENIA (Encuesta Nacional Industrial Anual), a plant-level manufacturing census from Chile that covers all establishments with more than 10 employees, for the time period 1998-2007.¹⁴ The data set is an unbalanced panel that contains detailed balance sheet and production information. Importantly, it specifies net after-tax firm income and corporate taxes paid by firms. We use these two variables to construct the average effective tax rates faced by firms, which is essential for our analysis. The advantage of this effective tax rate measure is that it summarizes all the subtleties of the tax code into one measure. One drawback is that there may be endogeneity between firm choices and characteristics and the firm specific tax rate. We perform several exercises to address this drawback and find that our results do not change.

To study the impact of firm-specific corporate tax rates on TFP, we develop a small open economy model where firms are heterogeneous in their productivity. Firms can choose whether to face a positive exogenous tax and have non-negative accounting profits or face a 0 percent tax and have non-positive accounting profits. This feature incorporates a specific exemption present in the Chilean tax code, which establishes that firms with non-positive profits face a corporate tax rate of 0 percent. This exemption is relevant since it affects around 20 percent of firms in our sample. By modeling this exemption, we intend to partially address the concern that firms' behavior can affect their effective tax rate. We also introduce firm-specific capital and output wedges to account for all other distortions and model misspecification. If we did not explicitly model the corporate tax rate, it would be accounted for by the capital and output wedges. By introducing it, we are stripping away its contribution to the wedges.

Using the data described above, we back out the capital and output wedges necessary to rationalize firms' observed choices of inputs. We then take these wedges as primitives and measure the change in aggregate output of implementing different flat tax policies relative to the observed tax policy. Last, we measure how much of this output change is generated by intrasectoral allocative efficiency, intersectoral reallocation of resources, and changes in the demand of resources. We define the contribution of intrasectoral allocative efficiency to the change in aggregate output as the TFP gap.

We find that if corporate taxes are removed, there is a positive TFP gap ranging from 4 to 11

¹⁴Different years of this data set have been used in several well-known studies, such as Liu (1993), Levinsohn and Petrin (2003), Oberfield (2013), Petrin and Sivadasan (2013), and Asker et al. (2014).

percentage points, depending on the year analyzed. Moreover, this gap decreases monotonically with the level of the flat tax rate and becomes negative after a threshold that varies with the year. We conclude that as the tax level increases, more resources are going to less productive firms. We also find that the revenue-neutral flat tax policy generates small changes in TFP. The contribution to the change in aggregate output of the intersectoral component is small relative to the TFP gap in every year and policy analyzed. Last, we perform several robustness checks to reinforce our results.

This chapter is related to an ongoing literature that tries to identify the main drivers of misallocation of resources and its effects on TFP.¹⁵ One factor analyzed in many studies is financial development. Examples of these studies are Midrigan and Xu (2014) and Gopinath et al. (2017). The quantitative impact of this factor on aggregate TFP varies depending on the study. For example, Midrigan and Xu (2014) find that the effect is at most 10 percent in South Korea. Gopinath et al. (2017) document an increase in capital misallocation in the south of Europe and find that financial frictions can explain this fact. The effect on TFP is around 3 percent. Another possible source of misallocation is firing costs. Hopenhayn and Rogerson (1993) find that imposing a one-year firing cost in the United States would lead to a 2 percent drop in TFP. This drop is due to the misallocation of labor across firms and changes in the establishment productivity distribution. We contribute to this literature by studying how the dispersion and level of corporate tax rates affect aggregate productivity. Moreover, we do this by using a direct measure of this friction. To the best of our knowledge, this is the first attempt to measure the effects of effective corporate tax rates on TFP through allocative efficiency at the firm level.

A strand of the literature argues that the dispersion in marginal products is a reflection of specific characteristics of the economic environment. David et al. (2016) study how information frictions show up as dispersion in marginal products. In their framework, firms face imperfect information when they make their input decisions and find losses in aggregate productivity for the United States, China, and India. Other environment specifications that yield dispersion in marginal revenue products are adjustment costs of capital, multiple production technologies, and different demand specifications.¹⁶ Although these restrictions could generate dispersion, they do not imply misallocation, as a benevolent planner would face these same physical constraints when allocating resources. In

¹⁵See Hopenhayn (2014) and Restuccia and Rogerson (2017) for a recent survey of this literature.

¹⁶Asker et al. (2014) find that adjustment costs can generate dispersion in marginal revenue products. Rossbach and Asturias (2017) analyze the impact of multiple production technologies on the dispersion of marginal products using the same data set used in our analysis. Haltiwanger et al. (2018) analyze how different demand specifications can show up as dispersion in revenue TFP.

our study, we take these factors into account by allowing corporate tax rates to interact with firm-specific output and capital wedges. These wedges are a reduced form of controlling for all frictions and model misspecification not accounted for in our theoretical framework.

Finally, this chapter contributes to the broad literature that studies the effects of effective corporate tax rates in macroeconomic aggregates. This literature mainly studies how corporate taxes affect investment and entrepreneurship. The general finding is that corporate taxation has significant adverse effects on both investment and entrepreneurship.¹⁷ One study that analyzes the Chilean economy is Hsieh and Parker (2007). The authors argue that the main cause of the investment boom in Chile in the last part of the eighties and nineties was due to a tax reform from 1984 through 1986 that cut the tax rate of retained profits from 50 percent to 10 percent. While these papers focus on investment and growth, our analysis is on the allocative effects of corporate tax rates.

2.2 Description of the Data

This section describes the data used in this chapter and presents facts about the effective corporate tax rate distribution in Chile.

2.2.1 The Annual Census of the Chilean Manufacturing Sector: ENIA

The data used are taken from the ENIA (Encuesta Nacional Industrial Anual), an annual census of the Chilean manufacturing sector. This data set is an unbalanced panel that covers all manufacturing plants with more than 10 employees and plants with less than 10 employees that belong to firms with multiple establishments. We use data for the period 1998-2007, as there were no reforms to the Chilean tax code in this time frame, except for pre-stipulated increases in the statutory tax rate. Table 10 shows the statutory tax rate for each year in our sample. After 2007, the ENIA's panel structure is eliminated, so that firms cannot be identified across years. For this reason, we do not use data after 2007, as doing so would have limited some of our quantitative exercises.

The ENIA collects data on revenue, net accounting profit, profit tax, employment, wage bill, fixed assets, and industry among other variables useful for our quantitative analysis. Previous versions of this census have been used in many studies, given its rich plant-level data. In Chile, the manufacturing sector accounted for roughly 17 percent of value added and 14 percent of employment for the period 1998-2007. Further details on the construction and representativeness of our

¹⁷See Djankov et al. (2010) and the references within.

sample can be found in Section B.1 of the appendix.

2.2.2 Profit Tax Facts in Chile

In this section, we document relevant tax facts about Chile. In Chile, all firms are subject to the same statutory tax rate, regardless of their level of profits. The ENIA collects plant-level data on net accounting profits and profit tax expenses. Using these two variables, we calculate the effective tax rate that each firm faces in a given year, as the ratio between profit tax expenses and gross accounting profits.¹⁸ For the years of our sample, the statutory tax rate increased from 15 percent to 17 percent. The effective profit tax rate that firms face has considerable dispersion, as seen in Table 10. This dispersion is generated by several exemptions outlined in the Chilean tax law, as well as fines for late payments and tax base revaluations to match economic activity with financial payments.

An important feature of the distribution of effective tax rates in Chile is that, on average, 30 percent of firms face a 0 percent tax rate. This feature is mainly driven by the tax code exemption that specifies that firms with non-positive accounting profits face a corporate tax rate equal to 0 percent.¹⁹ We also document that 75 percent of plants have an effective tax rate below or equal to the statutory tax rate, as can be seen in Table 10.

A plant may face an effective tax rate lower than the statutory tax rate because of loss carryforward, tax base revaluations, and other exemptions. Plants that face an effective tax rate that is higher than the statutory tax rate do so mainly for two reasons: late payment fines and tax base revaluations. Late payment fines range from 10 percent to 30 percent depending on how long it takes the plant to pay the amount owed. Plants also pay 1.5 percent interest per month on their debt. Taxes paid by tax base revaluations are technically called “deferred taxes”. These tax base revaluations arise from analyzing the differences, mostly temporary, between taxable and accounting profit.

¹⁸Gross accounting profits is the sum of profit tax expenses and net accounting profits.

¹⁹On average, 18 percent of the firms in our sample have non-positive profits.

Table 10: Distribution of Effective Profit Tax Rates (%)

Year	Statutory Tax Rate	25th percentile	50th percentile	75th percentile	90th percentile	Standard Deviation
1998	15	0	12.14	15.78	25.79	13.95
1999	15	0	12.03	15.63	24.81	13.90
2000	15	0	10.95	15.04	22.98	12.87
2001	15	0	9.69	15.01	22.06	12.79
2002	16	0	8.68	16.00	21.10	12.56
2003	16.5	0	11.31	16.58	23.19	13.44
2004	17	0	13.45	17.00	22.97	12.52
2005	17	0	14.08	17.02	22.76	12.86
2006	17	0	14.53	17.20	23.58	12.76
2007	17	0	13.99	17.11	24.08	13.19

The last column of Table 10 presents the standard deviation of corporate tax rates for every year of our sample. To address the issue that the dispersion in tax rates may be driven by tax exemptions targeted at firms with a specific characteristic, we decompose the variance of corporate tax rates into within-group and between-group components. We group firms by observables provided in the ENIA, such as size, region, industry, and business entity type. Table 11 shows the average share of the within- and between-group components of the variance of corporate tax rates. For all group categorizations considered, the within-group component accounts for more than 97 percent of the total variance.

Table 11: Variance Decomposition of Corporate Taxes (%)

Observable:	Within-Group Component	Between-Group Component
Size by Employment	98.79	1.21
Size by Sales	98.54	1.46
Size by Value Added	98.55	1.45
Region	99.15	0.85
Business Entity Type	97.14	2.86
Industry	98.77	1.23

Notes. This table portrays the share of the within-group and between-group components of the variance averaged for the period 1998-2007. Size categories for employment, sales, and value added are according to the standard categorization of the ENIA. There are 9 groups for employment and 10 groups for sales and value added. Firms are classified into 12 region groups and 8 types of business entities. Last, we group firms by two-digit industries according to the ISIC Rev. 3 industry classification.

2.3 Theoretical Framework

This section develops the theoretical framework that will allow us to evaluate the effect of corporate profit tax rates on resource allocations and its impact on TFP. We set up a standard monopolistic competition model with firm-specific output and capital wedges and firm-specific profit tax rates. We then explain the calibration of key parameters and the measurement of the variables that will be used in our quantitative analysis.

2.3.1 Monopolistic Competition Model

We consider a static monopolistic competition model with heterogeneous firms. We assume a small open economy with inelastic aggregate labor supply \bar{L} . There is a single final good Y produced by a representative firm in a perfectly competitive output market. The representative firm's production function is a Cobb-Douglas aggregator, and it uses output Y_s of industries $s \in \{1, \dots, S\}$ as inputs:

$$Y = \prod_{s=1}^S Y_s^{\theta_s}, \quad \sum_{s=1}^S \theta_s = 1, \quad (18)$$

and P_s is the price of industry s .

Industry output is a CES aggregator of M_s differentiated products with elasticity parameter σ :

$$Y_s = \left(\sum_{i=1}^{M_s} Y_{si}^{\frac{\sigma-1}{\sigma}} \right)^{\frac{\sigma}{\sigma-1}}. \quad (19)$$

Differentiated product firms are heterogeneous in their physical productivity, A_{si} . Their production function is given by

$$Y_{si} = A_{si} K_{si}^{\alpha_s} L_{si}^{1-\alpha_s}, \quad (20)$$

where K_{si} and L_{si} are the capital and labor inputs, respectively, and α_s is the capital share of industry s .

These firms maximize economic profit, which is the sum of accounting profit and the opportunity cost of capital. We make this distinction since corporate tax rates directly affect accounting profits. Note that in the data, a firm's tax rate is obtained as the product of the statutory tax rate and the tax base. A firm's tax base is a function of its accounting profits and the exemptions, deductions, and deferrals specified by the tax code. One exemption that we model explicitly is that firms with non-positive accounting profits face a 0 percent tax.

We model this exemption as follows. If a firm's accounting profit is non-negative, then the firm faces a profit tax rate, which we denote as t_{si} . This tax rate is exogenous and taken as given by the firm. On the other hand, if a firm has non-positive accounting profit, then its effective tax rate is equal to 0. Hence, a firm must choose whether to face a positive profit tax rate t_{si} and have non-negative accounting profit or a 0 profit tax rate with non-positive accounting profit.

Given this, the firm's problem is to maximize economic profit:

$$\pi_{si} = \max \{ \pi_{si}^t, \pi_{si}^0 \},$$

where π_{si}^t is the economic profit of a firm that faces profit tax rate t_{si} , conditioned on non-negative accounting profit, and π_{si}^0 is the economic profit of a firm that faces a profit tax of 0, conditioned on non-positive accounting profit. We express accounting profit as

$$\pi_{si}^A = P_{si} Y_{si} - w L_{si} - (\delta + \lambda r) K_{si} + \Gamma_{si}, \quad (21)$$

where λ is the fraction of capital that is financed by debt and Γ_{si} is non-operational income net of

non-operational costs.²⁰

If a firm faces profit tax rate t_{si} , economic profit π_{si}^t is

$$\pi_{si}^t = \max_{\{K_{si}, L_{si}\}} \pi_{si}^A (1 - t_{si}) - \tilde{\tau}_{Y_{si}} P_{si} Y_{si} - (1 - \lambda) r K_{si} - \tilde{\tau}_{K_{si}} (r + \delta) K_{si}$$

$$\text{s.t. } \pi_{si}^A \geq 0 \quad (\mu_{si}^t),$$

where μ_{si}^t is the Lagrange multiplier for the accounting profit's non-negativity constraint.

Maximization yields the following first-order conditions:

$$MRPK_{si} \equiv \alpha_s \frac{\sigma - 1}{\sigma} \frac{P_{si} Y_{si}}{K_{si}} = \frac{r (1 - \lambda t_{si} + \tilde{\tau}_{K_{si}} + \lambda \mu_{si}^t) + \delta (1 - t_{si} + \tilde{\tau}_{K_{si}} + \mu_{si}^t)}{1 - t_{si} - \tilde{\tau}_{Y_{si}} + \mu_{si}^t}, \quad (22)$$

$$MRPL_{si} \equiv (1 - \alpha_s) \frac{\sigma - 1}{\sigma} \frac{P_{si} Y_{si}}{L_{si}} = \frac{w (1 - t_{si} + \mu_{si}^t)}{1 - t_{si} - \tilde{\tau}_{Y_{si}} + \mu_{si}^t}. \quad (23)$$

If a firm faces profit tax rate 0, economic profit π_{si}^0 is

$$\pi_{si}^0 = \max_{\{K_{si}, L_{si}\}} \pi_{si}^A - \tilde{\tau}_{Y_{si}} P_{si} Y_{si} - (1 - \lambda) r K_{si} - \tilde{\tau}_{K_{si}} (r + \delta) K_{si}$$

$$\text{s.t. } \pi_{si}^A \leq 0 \quad (\mu_{si}^0),$$

where μ_{si}^0 is the Lagrange multiplier for the accounting profit's non-positivity constraint.

Maximization yields the following first-order conditions:

$$MRPK_{si} \equiv \alpha_s \frac{\sigma - 1}{\sigma} \frac{P_{si} Y_{si}}{K_{si}} = \frac{r (1 + \tilde{\tau}_{K_{si}} - \lambda \mu_{si}^0) + \delta (1 + \tilde{\tau}_{K_{si}} - \mu_{si}^0)}{1 - \tilde{\tau}_{Y_{si}} - \mu_{si}^0}, \quad (24)$$

$$MRPL_{si} \equiv (1 - \alpha_s) \frac{\sigma - 1}{\sigma} \frac{P_{si} Y_{si}}{L_{si}} = \frac{w (1 - \mu_{si}^0)}{1 - \tilde{\tau}_{Y_{si}} - \mu_{si}^0}. \quad (25)$$

²⁰The parameter λ is exogenous and constant across firms in our quantitative analysis. Γ_{si} allows us to match accounting profits in the model to those in the data. We assume that it is firm specific and does not depend on the input choices of the firm.

Similar to Hsieh and Klenow (2009) and Foster et al. (2008), we define revenue-based factor productivity as $TFPR_{si} \equiv P_{si} A_{si}$. Under a Cobb-Douglas production function, this can be expressed as

$$TFPR_{si} = \frac{\sigma}{\sigma - 1} \left(\frac{MRPK_{si}}{\alpha_s} \right)^{\alpha_s} \left(\frac{MRPL_{si}}{1 - \alpha_s} \right)^{1 - \alpha_s}. \quad (26)$$

From equations (22)-(25), we observe that firms' marginal products differ when they face different wedges and profit tax rates. Importantly, we assume that tax rates do not affect capital and output wedges. However, the tax rate interacts with the wedges in the marginal products of the firm. If we were to set wedges and taxes to zero, then all firms would have the same marginal products. Given this, equation (26) shows that revenue productivity would also equalize across firms. On the contrary, when firms face different wedges and profit taxes, there is dispersion in revenue productivity. Furthermore, firms with higher $TFPR_{si}$ are those that have higher wedges, raising their marginal products and lowering their capital, labor, and output levels.

The industry-weighted average of firms' revenue productivity, marginal product of capital, and marginal product of labor are denoted as \overline{TFPR}_s , \overline{MRPK}_s , and \overline{MRPL}_s , respectively. Using the above framework, we construct the aggregate measures for capital, labor, TFP, and output. First, we express the equilibrium allocations for sectoral resources, K_s and L_s , as

$$K_s = \sum_{i=1}^{M_s} K_{si} = K \cdot \omega_s^K, \quad (27)$$

$$L_s = \sum_{i=1}^{M_s} L_{si} = L \cdot \omega_s^L, \quad (28)$$

where $K = \sum_{s=1}^S K_s$ is aggregate capital, $L = \sum_{s=1}^S L_s$ is aggregate labor, ω_s^K is the sectoral share of capital, and ω_s^L is the sectoral share of labor. Sectoral shares have the following expression:

$$\omega_s^K = \frac{\alpha_s \theta_s / \overline{MRPK}_s}{\sum_{s'=1}^S \alpha_{s'} \theta_{s'} / \overline{MRPK}_{s'}} \quad (29)$$

$$\omega_s^L = \frac{(1 - \alpha_s) \theta_s / \overline{MRPL}_s}{\sum_{s'=1}^S (1 - \alpha_{s'}) \theta_{s'} / \overline{MRPL}_{s'}}. \quad (30)$$

We derive industry productivity as

$$TFP_s = \left[\sum_{i=1}^{M_s} \left(A_{si} \frac{\overline{TFPR}_s}{TFPR_{si}} \right)^{\sigma-1} \right]^{\frac{1}{\sigma-1}}. \quad (31)$$

Last, aggregate output can be expressed as a function of K_s , L_s , and TFP_s :

$$Y = \prod_{s=1}^S \left(TFP_s \cdot K_s^{\alpha_s} \cdot L_s^{(1-\alpha_s)} \right)^{\theta_s}. \quad (32)$$

2.3.2 Measurement and Calibration

We use the data described in Section 2.2.1 to calibrate the parameters of our model and measure firms' marginal revenue products and revenue productivities. Industries in the model correspond to the four-digit industries within the manufacturing sector according to the ISIC Rev. 3 industry classification. We measure firms' value added, $P_{si}Y_{si}$, as the difference between gross revenue and intermediate inputs. We use four-digit industry deflators for gross revenue and intermediate inputs, provided by the data set, to deflate our estimate of firms' value added. Industry value added, P_sY_s , is measured as the sum of all firms' value added within industry s . The capital input, K_{si} , is measured as the book value of fixed assets, which we deflate using the gross revenue deflators. To control for differences in human capital, hour requirements, and rent sharing across plants, we follow Hsieh and Klenow (2009) and use the wage bill deflated by the intermediate input industry deflator as the measure for labor, L_{si} . In a robustness check, we also consider hours worked for our measure of labor.²¹

As described above, we calculate effective tax rates as the ratio between a firm's profit taxes and its gross accounting profits. We denote the measured firm-specific effective tax rate as \hat{t}_{si} . Two things should be noted. First, we use average effective tax rates as marginal effective tax rates. The main advantage of following this method is that all exemptions and deductions of the tax code are embedded in our measure. Hence, we do not have to model the intricate details of the tax code. The main drawback of our approach is that the observed tax rate is potentially endogenous to certain firms' characteristics and past behavior. We conduct several robustness checks to verify that our results are not driven by other specific characteristics and behavior of the firm.

We set the rental rate of capital to $r = 0.05$ and the depreciation rate to $\delta = 0.05$, to make our

²¹ Due to data availability, we only carry out this analysis for the period 2001-2007.

results comparable with other papers in the literature. The elasticity of substitution between varieties is fixed at $\sigma = 3$, so that firms' price is 50 percent higher than their marginal cost. In Section 2.5.1, we evaluate the sensitivity of our results with respect to these assumptions. The capital share α_s in industry s is equal to 1 minus the labor share in that corresponding industry for the United States.²² These shares are obtained from the NBER Productivity Database.²³

Using the data and parameter values described above, we back out the capital and output wedges in the following manner. For firms with positive accounting profits, we use equations (22) and (23) to obtain the firm-specific wedges. Since $\mu_{si}^t = 0$, the output and capital wedges are

$$(1 + \tau_{Ksi}) = \frac{\alpha_s}{(1 - \alpha_s)} \frac{wL_{si}}{(r + \delta) K_{si}} (1 - \hat{t}_{si}) + \frac{(\delta + \lambda r) (\hat{t}_{si})}{(r + \delta)}, \quad (33)$$

$$(1 - \tau_{Ysi}) = \frac{\sigma}{\sigma - 1} \frac{wL_{si}}{(1 - \alpha_s) P_{si} Y_{si}} (1 - \hat{t}_{si}) + \hat{t}_{si}. \quad (34)$$

On the other hand, for firms with negative accounting profits the capital and output wedges are obtained from equations (24) and (25). In this case, $\mu_{si}^0 = 0$ and the wedges are²⁴

$$(1 + \tau_{Ksi}) = \frac{\alpha_s}{(1 - \alpha_s)} \frac{wL_{si}}{(r + \delta) K_{si}}, \quad (35)$$

$$(1 - \tau_{Ysi}) = \frac{\sigma}{\sigma - 1} \frac{wL_{si}}{(1 - \alpha_s) P_{si} Y_{si}}. \quad (36)$$

Last, we use equations (20) and (26) to calculate firms' physical productivity, A_{si} , and revenue productivity, $TFPR_{si}$, respectively. Using equations (27)-(32), we construct industry and aggregate measures of output, productivity, capital, and labor.

²²Following Hsieh and Klenow (2009), we set the capital shares for each industry equal to those of the United States as we suppose that the US economy is less distorted than Chile's economy.

²³Most data on firm labor payments do not include labor benefits such as social security contributions. In the same manner as Hsieh and Klenow (2009), we scale each industry's labor share by 3/2.

²⁴We cannot identify the capital and output wedges for firms that have accounting profits equal to 0, as we do not observe μ_{si}^0 in the data. We assume these firms face a tax rate of 0 and use equations (35) and (36) to back out the wedges. Although these wedges are mismeasured, this assumption only ameliorates the impact of corporate tax rates on resource allocation, as it gives more explanatory power to the output and capital wedges. Hence, our measure of the impact of effective tax rates on allocative efficiency is conservative. Firms with gross accounting profits equal to 0 only represent between 2 and 8 percent of the sample for the period analyzed.

2.4 Misallocation and Corporate Taxes

In this section, we use the framework developed above to analyze the impact of effective tax rates on allocative efficiency. First, we define the output gap as the change in output between two economies characterized by different wedges and tax policy, but holding the distribution of firm productivities constant. Then, we consider counterfactual tax policies and measure the implied output gap relative to the observed distribution of tax rates. We decompose this measure to analyze the effect on allocative efficiency of the observed effective tax rates. Finally, we analyze what happens with government revenue in our different counterfactuals.

2.4.1 Output Gap Decomposition

To study the impact of different tax policies, it is convenient to define the output gap between two economies that only differ in the wedges and effective tax rates each firm faces. We decompose this gap into five objects: the TFP gap, intersectoral capital reallocation, intersectoral labor reallocation, change in aggregate capital, and change in aggregate labor. The TFP gap reflects intrasectoral reallocation, as can be seen from equations (26) and (31). Capital and labor intersectoral reallocation are also affected by tax rates and wedges since the industry shares of capital and labor, ω^K and ω^L , are a function of firms' marginal products. Finally, aggregate capital demand changes for different tax rates and wedges through the marginal cost of capital. Note that by assumption, the aggregate demand on labor will not change since we have assumed a fixed aggregate labor supply.

Consider two economies that have different firm-specific output and capital wedges and profit tax rates but are equal in all other aspects. Denote the levels of output of these two economies by Y and \tilde{Y} . We refer to the output gap as the log percentage difference between these two levels of output. Using equations (27), (28), and (32), the output gap can be decomposed as follows:

$$\begin{aligned}
 \underbrace{\log\left(\frac{Y}{\tilde{Y}}\right)}_{\text{Output Gap}} &= \underbrace{\sum_{s=1}^S \theta_s \log\left(\frac{TFP_s}{\tilde{TFP}_s}\right)}_{\text{TFP Gap}} + \underbrace{\sum_{s=1}^S \alpha_s \theta_s \log\left(\frac{\omega_s^K}{\tilde{\omega}_s^K}\right)}_{\text{Intersectoral Capital Reallocation}} + \underbrace{\sum_{s=1}^S (1 - \alpha_s) \theta_s \log\left(\frac{\omega_s^L}{\tilde{\omega}_s^L}\right)}_{\text{Intersectoral Labor Reallocation}} \\
 &+ \underbrace{\sum_{s=1}^S \alpha_s \theta_s \log\left(\frac{K}{\tilde{K}}\right)}_{\text{Change in Aggregate Capital}} + \underbrace{\sum_{s=1}^S (1 - \alpha_s) \theta_s \log\left(\frac{L}{\tilde{L}}\right)}_{\text{Change in Aggregate Labor}}. \tag{37}
 \end{aligned}$$

Below, we analyze different counterfactual tax rates policies and compare them to the distribution of tax rates observed in the data.

2.4.2 Output Gap Decomposition and Corporate Taxes

In this section, we quantify the output gap decomposition using equation (37). We consider two economies that differ only in the tax policy implemented. Both economies are subject to the same firm-specific output and capital wedges. By doing this, we ensure that firms face the same frictions and model misspecification implied by the data in both economies. In one economy, we set taxes to $t_{si} = 0$, and in the other economy, we set taxes to the observed firm-specific profit tax rates, $t_{si} = \hat{t}_{si}$. This measures the change in output implied by modifying the actual Chilean tax policy to one with no corporate taxation, allowing us to quantify the effect of the dispersion and level of the observed tax rates on TFP.

Table 12 presents the results from the output gap decomposition. Moving to a counterfactual scenario with no corporate tax rates generates an increase in output that ranges from 20 percent to 38 percent, depending on the year considered. In all of the years analyzed, TFP increases due to the policy change. This increase ranges from 4 percent to 11 percent and is due to a more efficient intrasectoral allocation of resources. The effect on intersectoral reallocation is small. Intersectoral allocation of capital accounts for between -3 percent and 2 percent of the change in output. In three years, the effect of intersectoral allocation of capital is negative. Intersectoral allocation of labor increases in all years but only between 0 percent and 2 percent. Most of the change in the output gap is generated by large increases in the demand for aggregate capital. This is an implication of the small open economy assumption of the model. Setting $t_{si} = 0$ directly changes the cost of capital, which in this case generates large inflows of capital into the economy.

Table 12: Output gap decomposition: $t_{si} = 0$ (%)

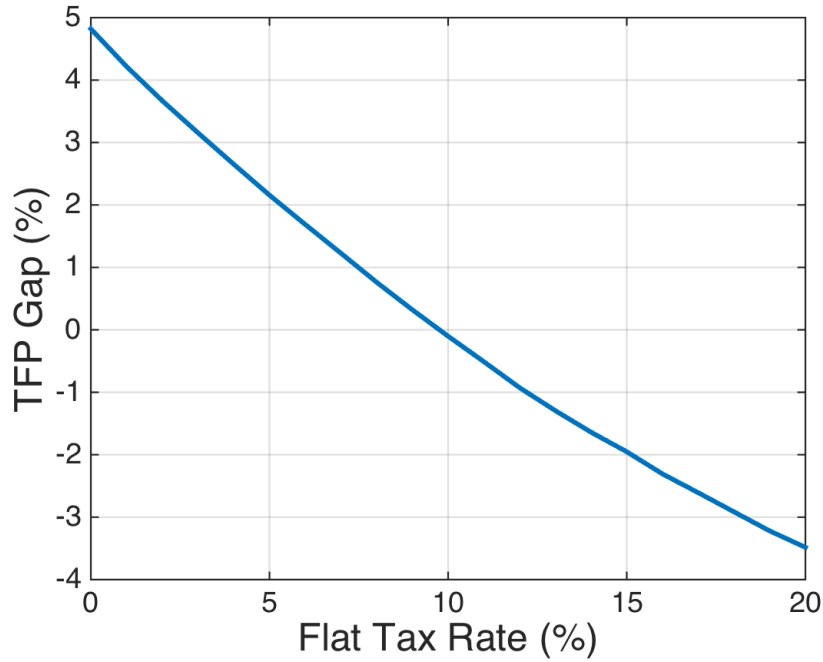
Year	Output Gap	TFP Gap	Intersectoral	Intersectoral L	Δ Aggregate
			K		Capital
1998	20.00	5.47	1.32	1.38	11.82
1999	21.20	6.43	0.41	1.05	13.31
2000	28.46	8.22	1.60	0.95	17.69
2001	22.79	5.64	0.10	0.72	16.33
2002	19.60	4.52	0.61	0.34	14.14
2003	19.85	4.82	0.03	0.55	14.45
2004	22.30	4.16	-0.41	0.80	17.75
2005	31.20	4.33	-2.94	1.74	28.07
2006	35.29	6.83	0.06	1.53	26.86
2007	38.02	11.12	-0.55	1.31	26.14

2.4.3 Allocative Efficiency and Corporate Tax Rates

In this section, we analyze how different levels of tax rates affect our economy by considering different counterfactual flat tax rate policies. The equations implied by the model portray the mechanisms through which intrasectoral reallocation of resources occurs due to different tax policies. Profit tax rates affect firms' marginal products, as can be seen from equations (22)-(25). Since profit tax rates interact with firm-level wedges, flat tax rate policies will have heterogeneous effects.

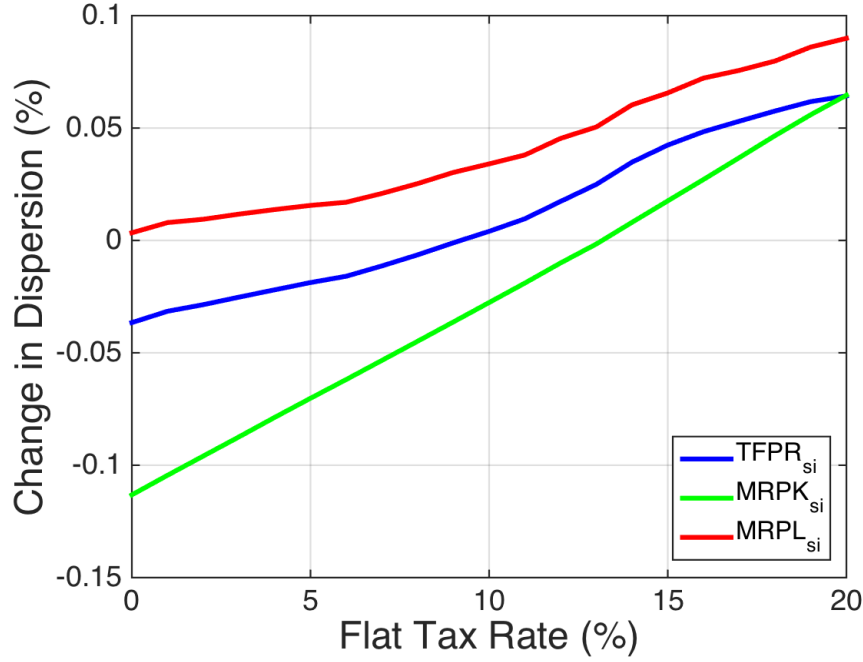
Our counterfactual exercise is the following. We set the corporate tax rate equal to \bar{t} for all firms (i.e., $t_{si} = \bar{t} \forall i$). In these counterfactual scenarios, all firms face the same output and capital wedges implied by the data as well as a flat tax rate \bar{t} . We compare these counterfactual economies to the observed Chilean economy and measure changes in allocative efficiency with respect to the data.

Figure 5: Relationship between TFP Gap and \bar{t} (2003)



The schedule in Figure 5 portrays the TFP gap between a counterfactual scenario with $t_{si} = \bar{t}$ and the observed Chilean economy $t_{si} = \hat{t}_{si}$, for different levels of \bar{t} , in the year 2003. This graph shows that the TFP gap decreases monotonically with the level of the tax rate, \bar{t} . This is the case for all the years studied in our sample. Furthermore, for lower levels of \bar{t} , the TFP gap is positive (TFP gains), while for higher levels of \bar{t} , this TFP gap becomes negative (TFP loss). In 2003, a flat tax rate policy of $\bar{t} = 0.0976$ would have generated the same aggregate TFP level as the one implied by the observed firm-specific corporate tax rates. This flat tax rate is lower than 16.5 percent, which was the statutory tax rate for that year. If in 2003 Chile had applied a flat tax rate policy at the statutory tax rate level without any exemptions and distortions, the loss in TFP would have been 2.46 percent. This remark is consistent for all the years in our sample.

Figure 6: Change in Dispersion Measures Relative to \bar{t} (2003)



Notes: The change in dispersion for revenue productivity is measured as the log difference between the standard deviation of revenue productivity implied by the flat tax rate policy and the standard deviation of revenue productivity implied by the observed tax rates. The same statistic is calculated for marginal revenue products.

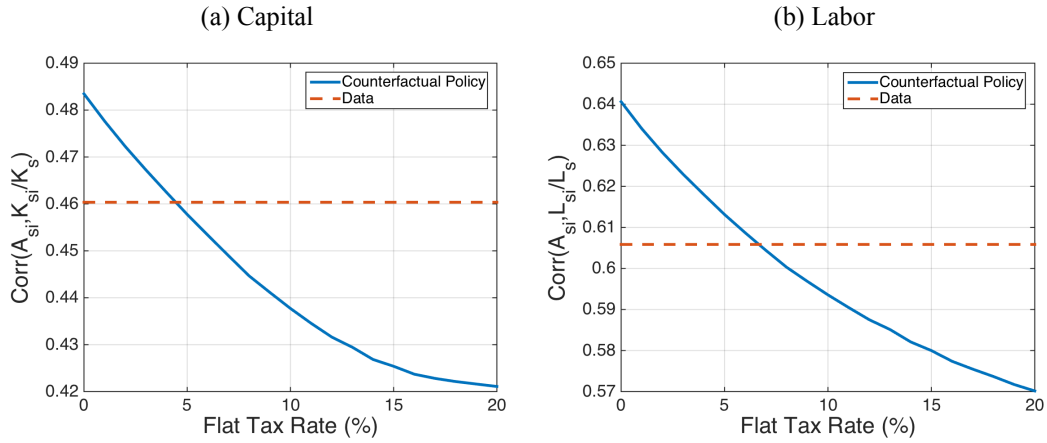
The monotonically decreasing relationship between the level of flat tax rates and the TFP gap can be explained as follows. For very small levels of flat tax rates, the dispersion in firms' marginal products and, hence, revenue productivity is lower. This has clear implications for aggregate TFP, as less dispersion in revenue productivity results in higher TFP. We can observe this mechanism in Figure 6, which shows the dispersion in marginal products and revenue productivity for counterfactual policy scenarios $t_{si} = \bar{t}$ relative to the dispersion in these measures in the data. As the level of the tax rate increases, the relative dispersion increases for both marginal products and revenue productivity. Intuitively, as the level increases, the profit tax rate amplifies the effects of the distortions and misspecification embedded in the output and capital wedges. As a result, dispersion in marginal products and revenue productivity increases, generating a lower TFP gap. This is the result of resources being allocated toward less productive firms within a sector.²⁵

To corroborate our results, we perform an alternative measure of allocative efficiency similar to

²⁵As a robustness check, we measure misallocation as in Olley and Pakes (1996) using our model outcomes. We find that the correlation of firm productivity with respect to both capital and labor shares within a sector drops as the tax levels increase.

Olley and Pakes (1996). Our results are summarized in Figure 7. In Panel (a), the schedule labeled “Counterfactual Policy” plots the correlation between firm productivity, A_{si} , and the share of firm i ’s capital stock, K_{si} , in sector s ’s capital stock, K_s , for different flat tax rate levels \bar{t} . Panel (b) plots the correlation between firm productivity, A_{si} , and the share of firm i ’s labor, L_{si} , in sector s ’s labor, L_s , for different flat tax rate levels \bar{t} . The dotted line labeled “Data” corresponds to the correlation measures for the observed Chilean data in 2003. The correlation of firm productivity with respect to both capital and labor share drops as flat tax levels increase, which shows that the intrasectoral reallocation mechanism described above drives the fall in the TFP gap. More resources are being allocated toward less productive firms.

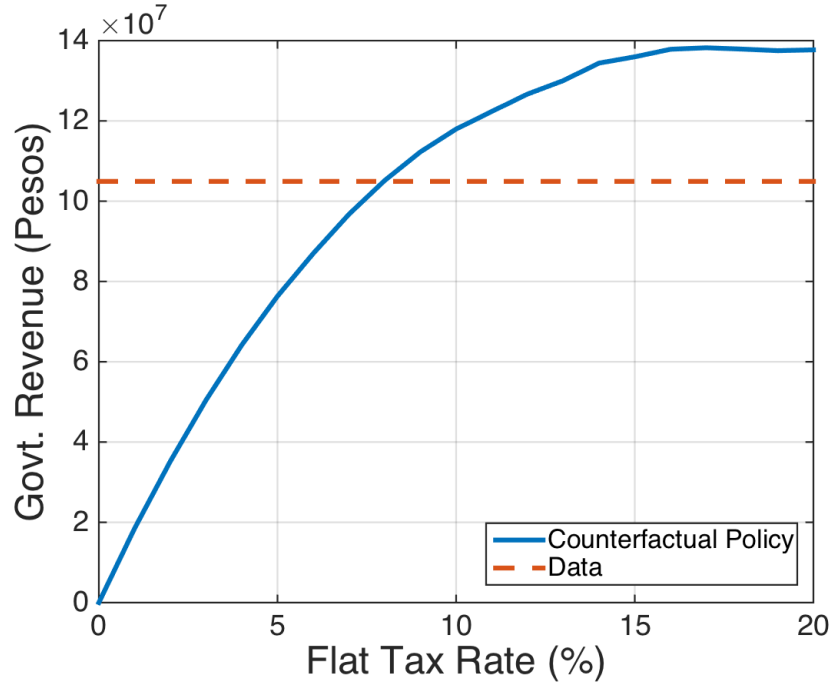
Figure 7: Correlation between Firm Productivity and Activity Share (2003)



Notes: The solid blue line labeled “Counterfactual Policy” corresponds to the correlation between firm productivity and firm activity share for different levels of \bar{t} . The dotted orange line labeled “Data” corresponds to the correlation between firm productivity and firm activity share in the data.

Next, we analyze the effect of these tax policies on government revenue. In Figure 8, the blue schedule labeled “Counterfactual Policy” portrays the Laffer curve for different flat tax rate policies. A clear trade-off stands out. Although very low flat tax rates yield higher levels of TFP, government revenue from corporate taxation is smaller. The dotted line labeled “Data” is the government revenue collected from the observed corporate tax rates. The flat tax rate policy that yields the same revenue is $\bar{t} = 7.97$ percent. If this policy had been implemented in Chile in 2003, then TFP would have increased by 0.77 percent. This pattern, however, is not found for all years in our sample. For some years in our sample, the revenue-neutral flat tax rate policy generates TFP gains with respect to the data, while for others it generates TFP losses.

Figure 8: Relationship between Government Revenue and \bar{t} (2003)



Notes: The solid blue line labeled “Counterfactual Policy” corresponds to the government revenue for different levels of \bar{t} . The dotted orange line labeled “Data” corresponds to the government revenue implied by the observed effective tax rates.

2.5 Sensitivity Analysis

In this section, we analyze the sensitivity of the results in Section 2.4 to our choice of parameter values and our measure of labor input.

2.5.1 Sensitivity to Parameter Values

Table 13 shows the TFP gap from eliminating corporate taxes for different interest rates r , depreciation rates δ , and values of σ , the parameter of the elasticity of substitution across varieties. For different interest rates, results are identical to the benchmark. As seen in equation (21), when $\lambda = 0$, the interest rate r does not affect the accounting profits of firms. Hence, it does not interact with the corporate tax rate in the marginal revenue products, as shown in equations (22)-(25). For this reason, different interest rates do not affect the TFP gap when corporate tax rates are eliminated. This is not the case anymore when we consider different values of λ .

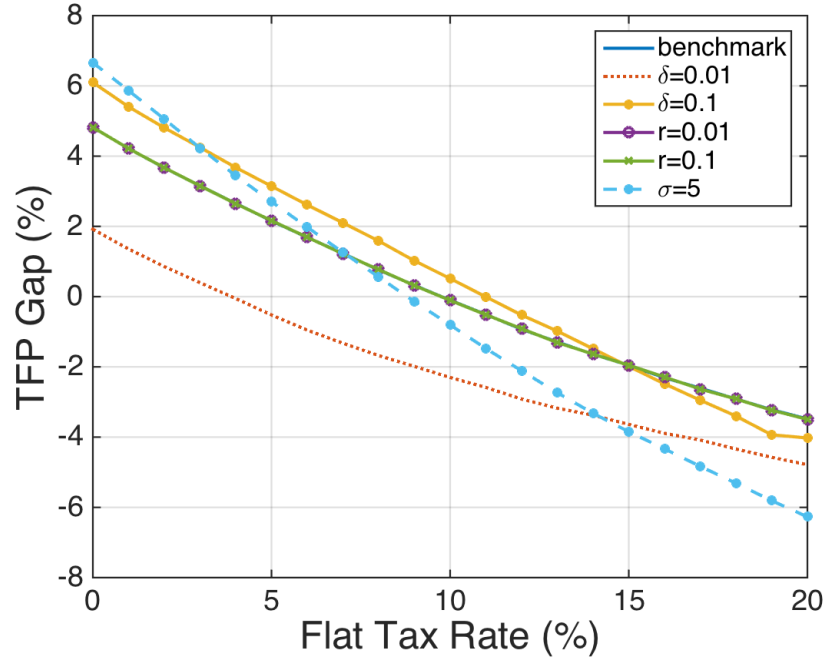
Table 13: TFP Gap for Different Parameter Values: $t_{si} = 0$ (%)

Year	Benchmark	$r = 0.01$	$r = 0.1$	$\delta = 0.01$	$\delta = 0.1$	$\sigma = 5$
1998	5.47	5.47	5.47	4.26	5.92	11.04
1999	6.43	6.43	6.43	0.93	7.90	11.43
2000	8.22	8.22	8.22	5.37	9.48	15.74
2001	5.64	5.64	5.64	0.86	7.49	9.98
2002	4.52	4.52	4.52	1.46	5.62	8.00
2003	4.82	4.82	4.82	1.92	6.10	6.66
2004	4.16	4.16	4.16	0.92	6.15	7.42
2005	4.33	4.33	4.33	-4.08	7.48	6.52
2006	6.83	6.83	6.83	2.32	8.52	10.08
2007	11.12	11.12	11.12	7.75	12.56	16.73

On the other hand, the depreciation rate has a direct impact on accounting profits, regardless of the value of λ . Moreover, as the depreciation rate increases, the TFP gains from eliminating corporate taxes are higher. Finally, we have chosen a conservative σ at the low end of the empirical estimates. Under $\sigma = 5$, the TFP gains are higher from moving from the observed corporate tax rates to a counterfactual scenario with no corporate taxation.

As in Section 2.4.3, we carry out the same flat tax rate policy counterfactuals. Our results are robust when we consider different parameter values for r , δ , and σ . Figure 9 shows the same decreasing relationship between the TFP gap the level of the tax rate, \bar{t} , as the one found in Figure 5.

Figure 9: Relationship between TFP gap and \bar{t} : Parameter Sensitivity (2003)

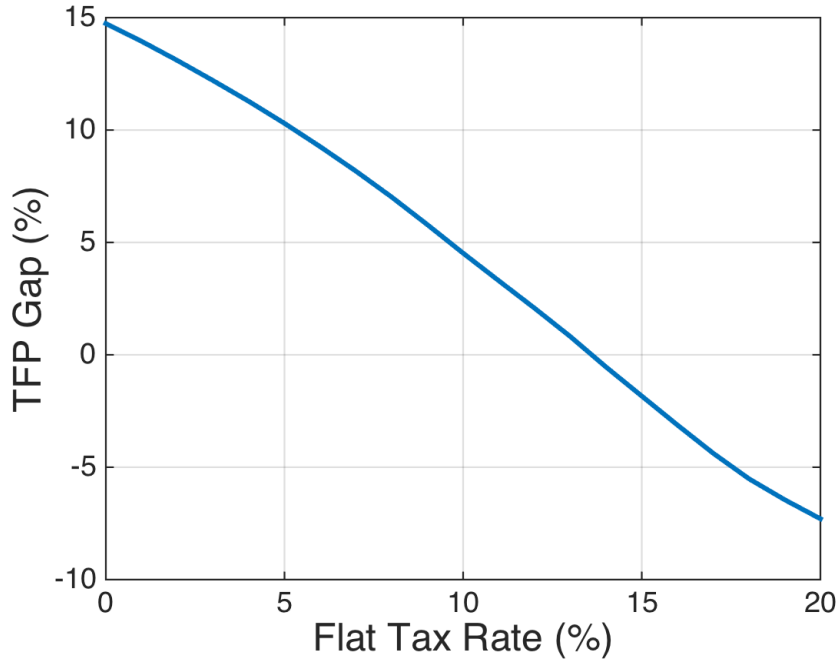


2.5.2 Hours Worked as Input for Labor

In the results described above, we measure L_{si} as the firm's wage bill. As a robustness check, we recalculate our estimates using hours worked as labor input.²⁶ Similar to Hsieh and Klenow (2009), using the wage bill for the labor input allows us to control for between-firm heterogeneity in rent sharing, skill level, and hours worked requirements. As these differences are not modeled in our framework, when we use hours as labor input, they are loaded into the output and capital wedges. As a result, dispersion in $TFPR_{si}$ is higher.

²⁶The data set analyzed has hours worked only for the years 2001-2007.

Figure 10: Relationship between TFP Gap and \bar{t} : Hours as Labor Input (2003)



Repeating our exercise with hours as labor input yields two main findings. First, in line with the results in Section 2.4.3, the TFP gap falls when we increase the level of the corporate tax rate, as seen in Figure 10. Second, the TFP gap across different counterfactual policies is larger. This is because our results are amplified since the corporate tax rate interacts with output and capital wedges, which are more dispersed for the reasons mentioned at the beginning of this section. This result holds across all years of our sample, as seen in the output gap decomposition in Table 24 in the appendix.

2.6 Robustness Checks on the Measurement of Effective Tax Rates

Given that we use average tax rates in our analysis, there is concern about the endogeneity of firms' characteristics and choices with our measure of the observed profit tax rate. To address this concern, we conduct several robustness checks. First, we address the issue of loss carryforward by firms, which could explain our results since we are considering a static model. Second, we analyze what would happen if all capital was financed with debt, which would change the financing structure of the firm and lower accounting profits, since interest can be subtracted. Third, we repeat our analysis with the permanent sample of firms. By doing this, we discard the possibility that special tax incentives

of young or old firms may be driving our results. As shown below, we find that our results do not vary when taking these issues into account.

2.6.1 Financing Capital with Debt

So far, we have assumed that capital is financed entirely with equity, $\lambda = 0$. This is a strong assumption since firms may finance capital with a mix of capital and debt. Firms have incentives to finance capital with debt since interest payments are discounted from accounting profits and therefore lower the tax that firms must pay. In this section, we analyze the other extreme case in which all capital is financed with debt $\lambda = 1$ to determine whether our results are sensitive to this assumption. Note that our calculation of the effective tax rate that firms face is not affected by the capital structure decision of the firm since we observe profits net of interest and taxes. Hence, the tax rate we calculate already takes into account the firm's capital structure. However, our results will vary depending on the amount of capital a firm finances with debt, since λ interacts with the effective tax rate t_{si} in the marginal revenue product of capital.

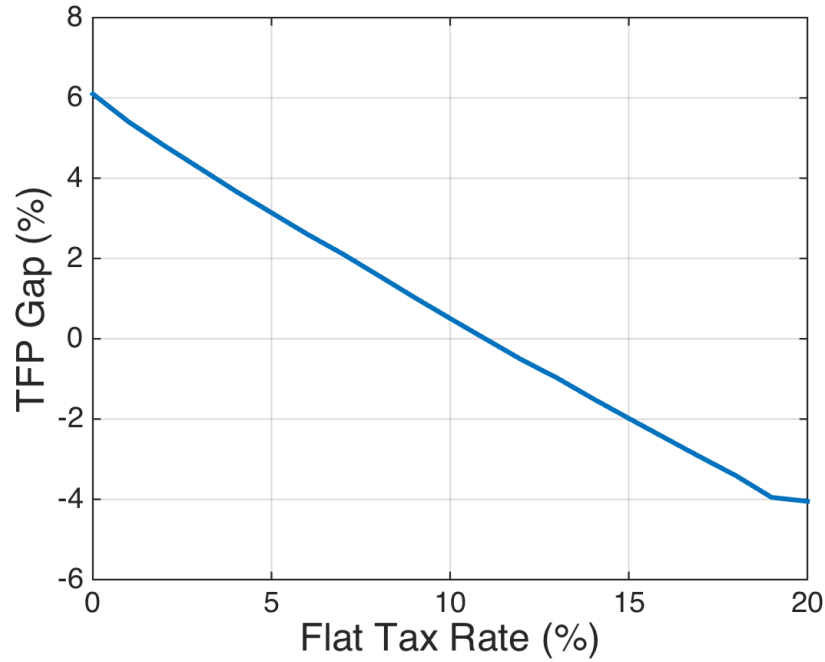
Note that if we observed profits before subtracting interest and taxes instead of using profits net of interest and taxes, differences in access to credit and other distortions that may affect the capital structure would also be loaded into the effective tax rate instead of the capital and output wedges. Also, it is important to note that the fraction of capital financed with debt can potentially be firm specific. For example, some firms may have better access to credit than others. Uras (2014) explores this mechanism and finds that it has important implications for capital misallocation. In our setup, these differences in access to credit are reflected in the capital and output wedges.

Table 14: Output gap decomposition: $\lambda = 1$, $t_{si} = 0$ (%)

Year	Output Gap	TFP Gap	Intersectoral		Δ Aggregate Capital
			K	Intersectoral L	
1998	16.58	5.92	1.72	1.34	7.60
1999	17.51	7.90	1.31	1.00	7.30
2000	24.10	9.48	1.91	0.97	11.74
2001	18.75	7.49	0.85	0.71	9.70
2002	15.90	5.62	1.43	0.34	8.51
2003	16.79	6.10	1.13	0.52	9.03
2004	19.09	6.15	0.78	0.79	11.38
2005	26.57	7.48	0.16	1.68	17.26
2006	31.18	8.52	0.64	1.52	20.50
2007	34.54	12.56	0.58	1.29	20.11

Table 14 shows the output gap decomposition under $\lambda = 1$ and under the scenario in which corporate tax rates are equal to $t_{si} = 0$. Results are very similar to those of Table 12. The increase in output from eliminating the effect of dispersion and level of corporate taxes is mainly explained by an increase in aggregate capital demand and an increase in TFP. Hence, we can see that intrasectoral reallocation of resources plays a significant role in explaining the output gap, while intersectoral reallocation of resources has a negligible effect on the output gap. This finding is consistent with the results found in Section 2.4.2.

Figure 11: Relationship between TFP Gap and \bar{t} : $\lambda = 1$ (2003)



As in Section 2.4.3, we carry out different counterfactual flat tax rate policies and evaluate their relationship to the TFP gap. In Figure 11 we can observe the same pattern as in Figure 5. As the flat tax rate level increases, the TFP gap falls. Also under the assumption that $\lambda = 1$, the dispersion of marginal products and revenue productivity increases as the flat tax rate levels increase. Higher flat tax rates exacerbate the effect of output and capital wedges, generating the increase in dispersion. Furthermore, as in Section 2.4.3, this increase in the dispersion of revenue productivity is a result of resources reallocating from more productive firms to less productive firms as the flat tax rate increases.

2.6.2 Accounting for Loss Carryforward

One of the exemptions that generate dispersion in effective corporate tax rates is the fact that plants can carry forward losses from one period to the next to reduce their tax base. Firms optimally choose capital and labor taking into account that this exemption allows them to reduce their tax burden. However, we do not model this explicitly since our analysis is static, and thus this specific source of distortion is loaded into the wedges. To measure how sensitive our results are to this omission, we

consider the following exercise. We take the average across years for each plant's relevant variables and estimate the TFP gap for our policy counterfactuals. By doing this, any losses that could have been carried forward will smooth out. Note that if all the dispersion in effective tax rates was due to this channel, the tax rates that firms face in this exercise should be less dispersed and similar to the statutory rate. This is not the case, however, as the effective tax rate calculated by averaging profit and profit tax across years is distributed similarly to the effective tax rates calculated year by year. We can see this by comparing Tables 10 and 15.

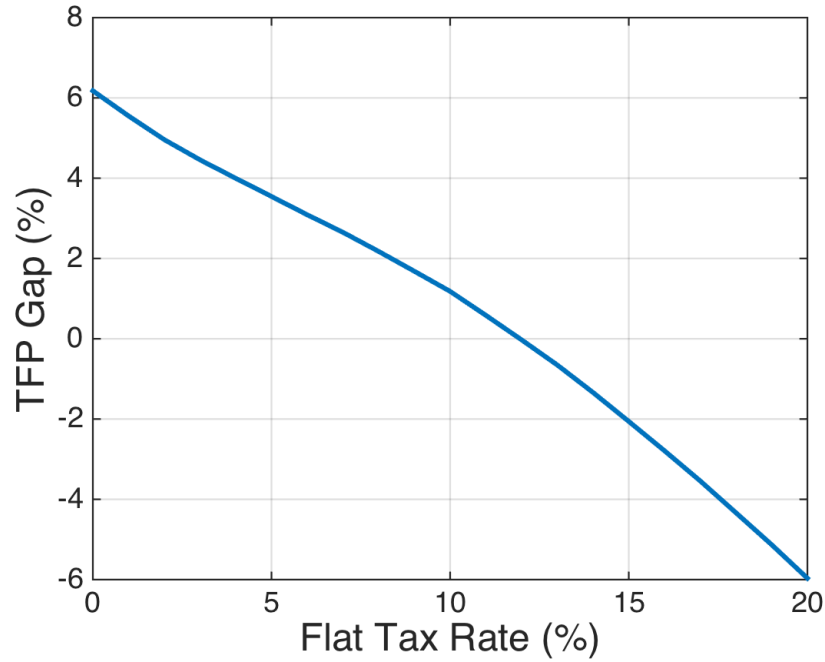
Table 15: Distribution of Effective Profit Tax Rates: Loss Carryforward (%)

25th percentile	50th percentile	75th percentile	90th percentile	Standard Deviation
1.34	12.82	16.45	20.33	11.00

Our results for this exercise are similar to our benchmark results. The decomposition of the output gap when firms face $t_{si} = 0$ can be seen in Table 25 in the appendix. When firms do not face corporate tax rates, TFP increases by 6.18 percent, which is within the range of values of our benchmark analysis, as seen in Table 12. Hence, loss carryforward is not the main driver of the distortions generated by heterogeneous tax rates. Similar to Section 2.4.2, intersectoral reallocation of resources accounts for a very small portion of the output gap, while changes in aggregate capital demand play a more significant role.

As in the benchmark, we also carry out flat tax rate counterfactual policies and measure their effect on aggregate TFP. We find that the negative relationship between the TFP gap and the flat tax rate level still persists, as seen in Figure 12. Hence, despite eliminating the dispersion in corporate tax rates coming from loss carryforward, as the flat tax rate increases, resources are allocated from more efficient firms to less efficient firms.

Figure 12: Relationship between TFP Gap and \bar{t} : Loss Carryforward (2003)



2.6.3 Permanent Sample

Dispersion in corporate tax rates can potentially be driven by tax exemptions given to young entrant firms, which are usually directed at fostering industry competition. If this is the only source of tax rate dispersion and entrant firms are relatively less productive than incumbent firms, then these tax exemptions would be responsible for the positive TFP gap shown in Table 12. Intuitively, these tax exemptions would be allocating more resources to less productive entrant firms and fewer resources to more productive incumbent ones. Hence, if Chile moved to a tax policy with no corporate taxes, then resources would reallocate to the more productive incumbent firms, generating the positive TFP gap.

To control for this mechanism, we focus on the firms that were always in operation for the period 1998 to 2007 and then perform the output gap decomposition for the years 2003 to 2007. By doing this, we make sure that the firms had been in operation at least five years.²⁷ If the only source of tax rate dispersion was exemptions to less productive entrant firms, then when we eliminate them from

²⁷ We also perform the analysis for the years 1998 to 2002, and the results are very similar.

the sample, the TFP gap would be 0. This is not the case, however, as can be seen in Table 16, which implies that there are other sources of corporate tax rate dispersion that generate a positive TFP gap. In this exercise, we also control for the fact that less productive exiting firms are driving our results, since the permanent sample comprises highly productive firms that have been operating for at least 10 years.

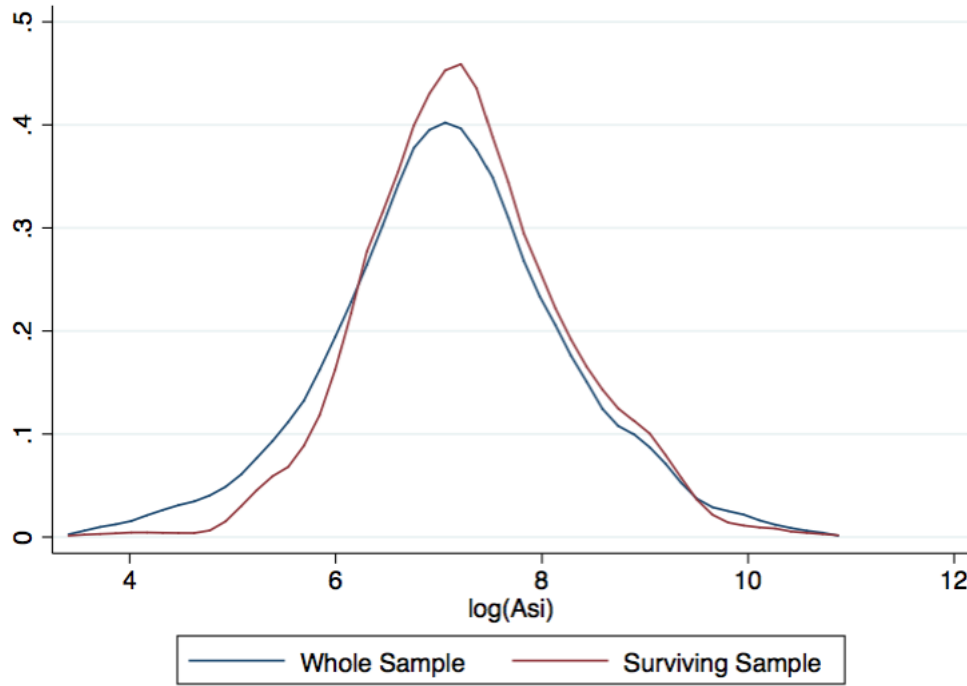
As shown in Table 26 in the appendix, there is significant dispersion in the effective corporate tax rates faced by the firms in the permanent sample for all years. Hence, tax exemptions given to young firms are not the main driver of this dispersion.

Table 16: Output Gap Decomposition: Permanent Sample, $t_{si} = 0$ (%)

Year	Output Gap	TFP Gap	Intersectoral	Intersectoral L	Δ Aggregate
			K		Capital
2003	19.23	2.63	-0.08	0.75	15.98
2004	22.40	4.32	0.16	1.29	16.99
2005	22.96	3.54	-0.09	1.36	18.13
2006	27.75	4.74	-0.91	2.18	21.72
2007	26.36	5.36	-0.20	1.68	19.51

By comparing Table 16 with Table 12, we can see that the results for intersectoral reallocation of resources and changes in input demands are similar. Also, we can observe that the TFP gap from eliminating corporate taxes is smaller in the permanent sample in comparison to the whole sample. The main reason for this finding is that the permanent sample controls for firm entry and exit. Firms in this sample had been in operation for at least 10 years in 2007. Hence, they were relatively more productive than the firms that entered or exited the sample during the time period we analyze. We document this finding in Figure 13, in which we compare the distribution of $\log(A_{si})$ for the whole sample in comparison to the permanent sample for 2003.

Figure 13: Distribution of $\log(A_{si})$ for the Whole and Permanent Samples



We find that the mean of $\log(A_{si})$ is higher in the permanent sample in comparison to the whole sample. Moreover, the distribution of the permanent sample has a much thinner left tail and is more concentrated around the mean. This pattern occurs in all the years between 1998 and 2007. This is evidence that the firms that exit every year tend to be the least productive firms, while the more productive firms remain. As a result, the gains from reallocation of resources in the permanent sample are smaller than in the whole sample.²⁸ Last, it is important to note that for the permanent sample, the TFP gap is also decreasing in the level of flat tax rates, as seen in Figure 29 in the appendix.

2.7 Conclusion

The objective of this chapter is to quantify the effects of corporate tax rates on aggregate TFP through allocative efficiency. To do this, we set up a standard monopolistic competition model that includes firm-specific corporate tax rates as well as output and capital wedges. In our framework, firms can choose whether to face a positive tax rate and have non-negative accounting profits or face a tax

²⁸This finding is consistent with what Gopinath et al. (2017) find when analyzing Spanish firm-level data.

rate of 0 percent and have non-positive accounting profits. We incorporate this exemption from the Chilean tax code to address the caveat that firms' behavior can affect the effective tax rate they face. We calibrate the model and find that if Chile had eliminated corporate tax rates, then TFP would have increased between 4 percent and 11 percent for the period 1998-2007. We also analyze how different levels of flat corporate tax rates affect TFP in an economy characterized by other distortions. We show that there is a monotonically decreasing relationship between the TFP gap and the level of the flat tax rate. We carry out a sensitivity analysis on parameters and robustness checks on our measure of effective tax rates and find that our results do not vary.

3 Demographics, Labor, and the Great Recession

3.1 Introduction

Recent literature has reached the consensus that after the Great Recession, output and labor in the United States diverted from their pre-crisis long term trends. Although many theories are trying to explain the sources of these patterns, one plausible candidate is demographics. The start of the crisis coincided with the “baby boomers” entering age cohorts associated with lower levels of labor force participation and retirement. Hence, this shift in the demographic composition has the potential of explaining the observed economic activity during the recovery.

The objective of this chapter is to quantify the effects demographic changes had on the evolution of output and labor in the recovery period after the Great Recession. For this, we first carry out an in depth analysis of employment trends for the time period 1990 - 2015. We document that a significant portion of the literature is incorrect when comparing the evolution of labor after the crisis with its pre-crisis trend. More specifically, we construct a counterfactual trend in which we account for demographic effects on the intensive margin, number of hours worked, and the extensive margin, labor force participation. We find that our counterfactual trend of employment, which accounts for demographics, reduced the gap in between the pre-crisis employment trend and the data by 83.7%.

Given this evidence of the potential effects of demographics on labor supply, we develop a growth model that incorporates demographics. More specifically, demographics affect the dynamics of the model through the growth rate of population and through changes in the age distribution of the population across time. We calibrate this model to match moments of the US pre-crisis economy.

Using this model, we first analyze how much demographics would have accounted for changes on output and labor in absence of the Great Recession. We document that 35% of the output gap between the pre-crisis trend and the data is explained by demographics. The channel through which demographics affect output is through a reduction in the hours worked by agents in the model. We then expand our analysis to also include fluctuations in total factor productivity. We find that this specification is able to reduce the gap in between output in the model and output in the data to 2.5%. Furthermore the gap in between labor in the model and in the data reduces to 1.2%.

3.2 Literature Review

This chapter is related to two main branches of the literature: the Great Recession and Demographics. Since 2008, many hypotheses have tried to understand the reasons behind the slow recovery in aggregate output and employment for the United States. Hall (2015) quantifies the contribution of different factors to explain their role in the slow recovery of aggregate variables. He documents that through 2013, output was 13 percentage points below its 1990 - 2007 trend, where the main contributors to this gap were the fall in business capital, productivity, and labor force participation.

From a more theoretical standpoint, the causes and mechanisms behind the Great Recession have been broad. For example, Schaal and Taschereau-Dumouchel (2015) set up standard neoclassical growth model with monopolistic competition and coordination failures to explain long recessions. They find that a big transitory shock, like the one in 2007, can force the economy into a steady state characterized by lower output and employment. On the other hand, Shimer (2012) sets up a search model with real wage rigidities to explain jobless recoveries. He documents that the interaction of rigid wages with search frictions are important for a persistent slow recovery in economic activity. Heathcote and Perri (2018), Mian and Sufi (2011), Mian and Sufi (2012), Mian et al. (2013) and Midrigan and Philippon (2011) study mechanisms by which a fall in housing prices, housing net worth, and tightening of credit standards caused declines in household debt, consumption and employment. This chapter is similar to these in the sense that it tries to understand the reduction in output and employment that occurred after the crisis of 2007. It differs from these as it tries to quantify the role of demographics in explaining the fall in output and labor.

The discussion on demographics and its effects on growth and employment has been increasing in the past few years in the literature. First, Hayashi and Prescott (2002), Chen et al. (2005), and Chen et al. (2006), modify the standard growth model to account for dynamics in exogenous variables such as the growth in population. Among the caveats of only considering population growth in the standard neoclassical growth model is that demographics only affect the household by increasing its size across time. In other words, population growth does not take into account possible effects of changes in the population distribution across age groups as well as differences in agents' decision making at different age groups.

Using an empirical approach, Maestas et al. (2016) find that the effects of the population's age structure has an important impact on output per capita growth for the US. They document that a 10% increase in the population above 60 years causes a decrease in 5.5% in the growth rate of GDP

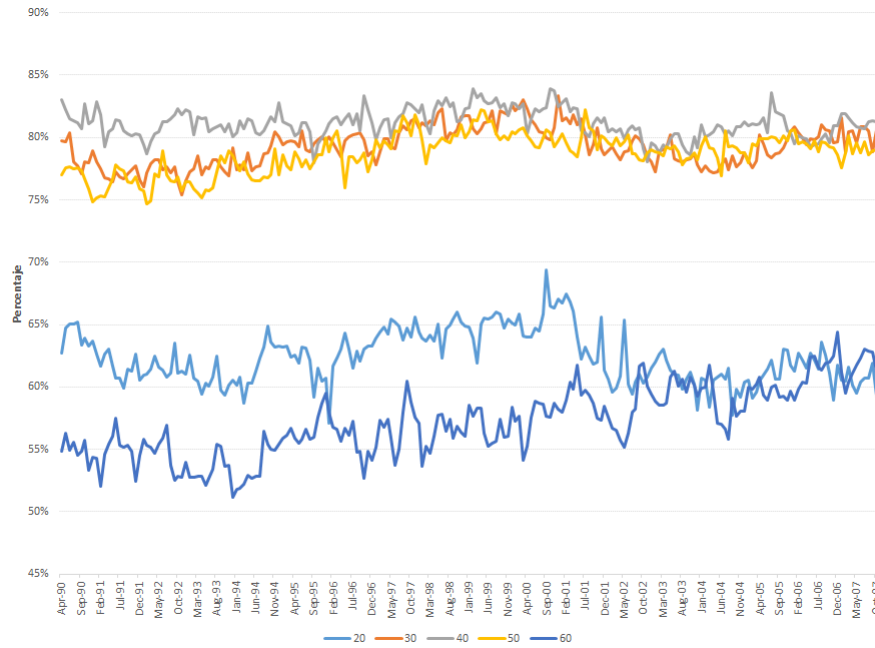
per capita. Given these aspects, we consider a modification of the standard growth model, which accounts for differences in the population composition of age groups across time.

Since the Great Recession, there has been a bigger discussion on the relationship in between demographics and labor supply. In his quantitative approach, Hall (2015) estimates that of the 13 percentage point drop in output, 1.1 was explained by the effect of the aging of baby-boomers on labor force participation. Maestas et al. (2016) find that of the 5.5% reduction in the output growth rate caused by demographics, two-thirds is a result of slower growth in labor productivity of workers across the age distribution, while the rest is a result of slower growth in the labor force. To our knowledge, the closest work analyzing the effects of demographics on labor supply is by Cooley and Henriksen (2018). They set up a life-cycle model to examine how demographic induced changes in the intensive (hours worked) and extensive (employment) margins of labor supply affect the slow-down in output growth. This chapter differs to the aforementioned, as we analyze the specific effects that demographics have on macroeconomic aggregates through the lens of a modified growth model.

3.3 Employment Trends

We use monthly micro data from the Current Population Survey (CPS) obtained from the Integrated Public Use Microdata Series, IPUMS. To understand the effects of demographics on labor supply and output after the great recession, we start our analysis by documenting stable labor patterns before the crisis, for the period 1990 - 2007. We focus on this time period for the following reasons. We exclude the period before 1990 because women employment rate was raising as a consequence of the increase of their participation in the labor force. Additionally, after 2007, the Great Recession had a negative impact on labor.

Figure 14: Employment Ratio by Cohorts



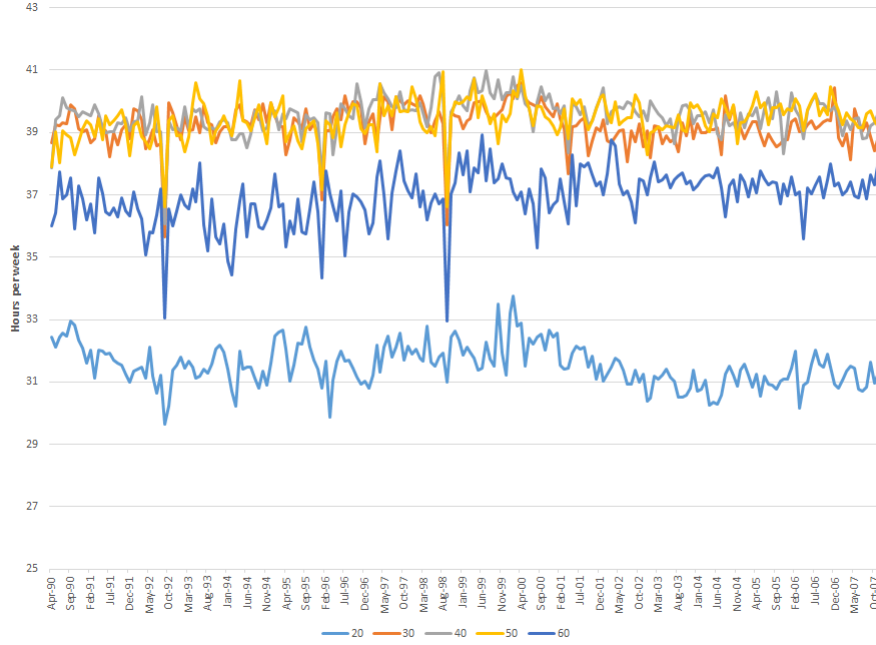
Source: Current Population Survey

We analyze employment and hours worked by age cohort in between 1900 and 2007. For each cohort, we observe the number of workers, and the total amount of hours worked. As Figure 14 shows, there is a stable evolution of the employment ratio (E_t^a), measured as the ratio of employment to population. For example, the monthly employment ratio for workers with age 40 fluctuated in between 78% and 83%; similar patterns are found across age cohorts. We estimate the average hours worked by those employed in each cohort (h_t^a), as the ratio of total hours to the total number of employed in each age group. Figure 15, shows that this statistic is also stable over time.

To statistically test for the stability in the employment ratio and hours worked, we fit a line through the time series of these statistics (linear regression). We find that the slope of the linear regression is statistically zero for most years between 25 and 50 years old. The slope is statistically negative for younger cohorts, and positive for older cohorts. However, in both cases the slope is relatively small²⁹.

²⁹The slope coefficient is statistically significant for ages 15 to 20 (negative) and above 55 (positive). On average the slope for younger cohorts implies a 2.7% decrease of employment ratio over 10 years, and for older cohorts implies an increase of 3.4% over 10 years.

Figure 15: Average Hours Worked by Cohort



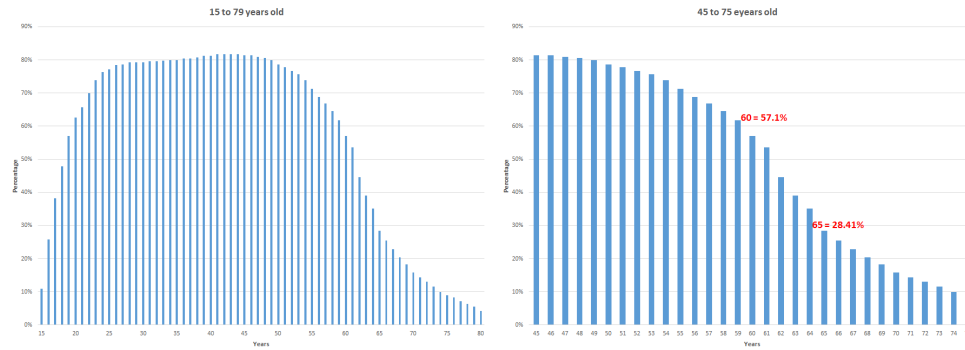
Source: Current Population Survey

Using these statistics of the employment ratio and average hours worked, we construct a counterfactual of the total hours worked in the absence of the Great Recession. The motivation for this is to have an aggregate labor measure that allows us to compare the actual data to what would have happened without the crisis. We calculate the counterfactual in the following manner. Given the stability of the employment ratio and average hours worked for every cohort, we calculate the average of these measures across time as in equations (38) and (39):

$$\bar{E}^a = \frac{1}{T} \sum_{t=1990:2}^{2007:4} E_t^a, \quad (38)$$

$$\bar{h}^a = \frac{1}{T} \sum_{t=1990:2}^{2007:4} h_t^a. \quad (39)$$

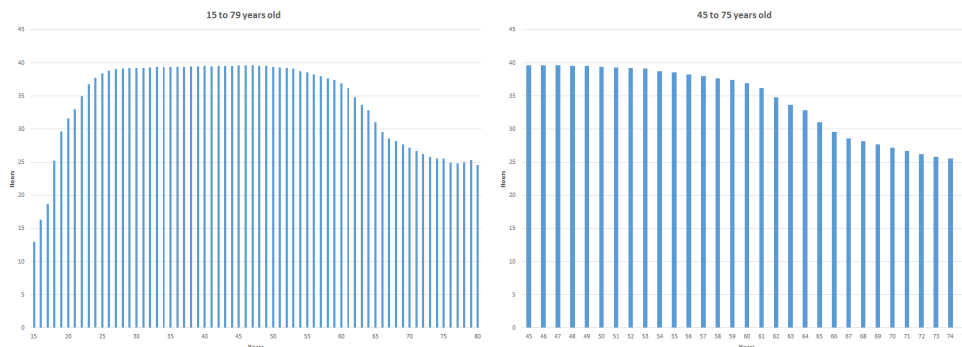
Figure 16: Average Employment Ratio by Cohorts



Source: Authors' calculation with data from CPS.

Figures 16 and 17 plot these statistics for every age group. The patterns portrayed in Figures 16 and 17 are similar. For young cohorts, the employment ratio is lower as most individuals in these cohorts are most likely with schooling responsibilities. For the case of average hours worked, young individuals also work a smaller number of hours, a result that is most likely due to their time being allocated to schooling. For age cohorts above 60, we can see that there is a fall in both employment ratio and average hours worked. As expected, older individuals begin to retire at around the age of 60, which causes the employment ratio to fall. More specifically, in between the ages of 60 and 65, the average employment ratio falls in about 30 percentage points. Also, the average hours worked falls for older individuals; in between the ages of 60 and 65, the average hours worked falls in more than 5 hours. Hence, older cohorts would affect aggregate labor supply through the extensive margin, by choosing to not supply labor, and the intensive margin, by choosing to work less hours.

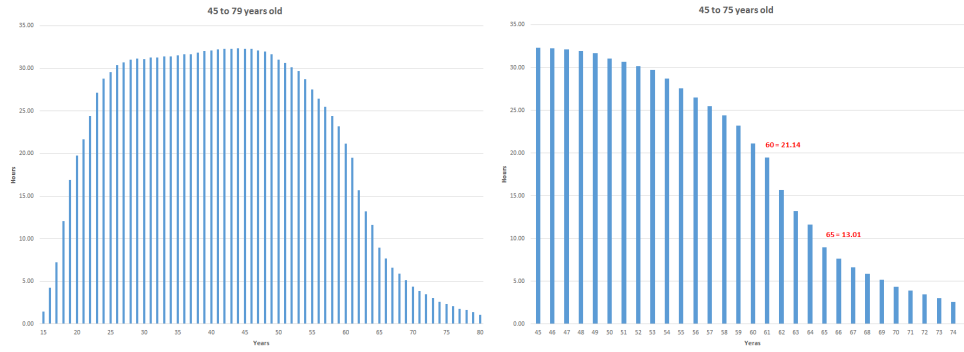
Figure 17: Average Hours Worked by Cohorts



Source: Authors' calculation with data from CPS.

The product in between \bar{E}^a and \bar{h}^a yields the number of hours worked per person in age cohort. Figure 18, shows this product. For older cohorts, there is a stronger decline in the number of hours worker per person in contrast to the average hours worked, as a consequence of labor supply falling through the extensive and intensive margins. Comparing the age cohort of 60 to that of 65, there is a decrease in the number of hours worked per person of more than 12 hours (58% drop).

Figure 18: Number of Hours Worked per Person by Cohorts



Source: Authors' calculation with data from CPS.

Focusing our analysis on the drop of labor supply of older cohorts is important, as it is a potential explanation of the apparent slow recovery of hours after the Great Recession. The years of the crisis coincide with the start of the baby boomer generation entering older cohorts and leaving the labor force. As a result, demographics played an important role during the years of the Great Recession, as they did in the 1980s and 1990s, when the baby boomers were at their most productive stage of their lives.

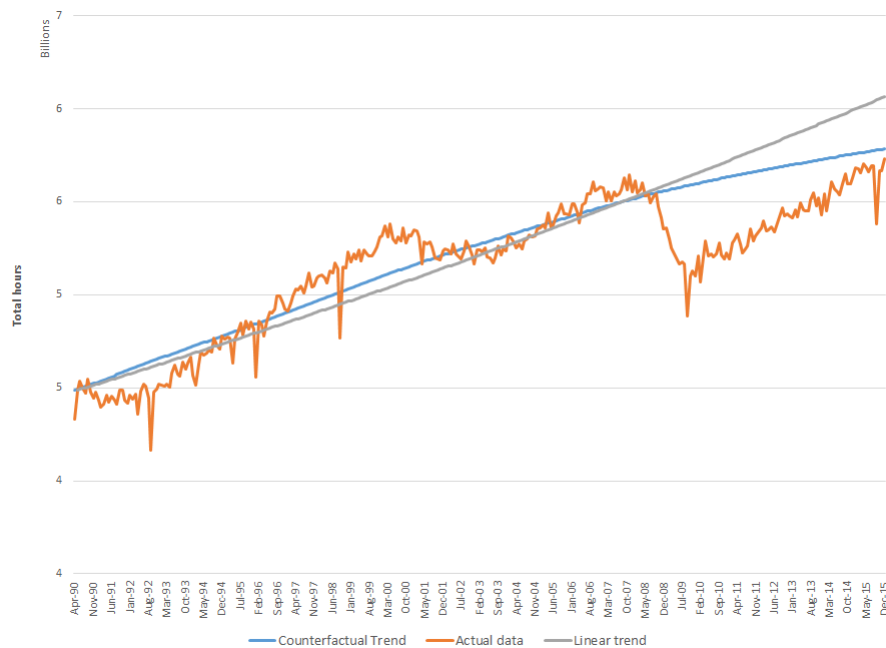
Next, we construct the total hours worked for the time period analyzed above 1990 - 2007, as well as the time period afterwards, 2008 - 2015. For each year t , we multiply the product in between \bar{E}^a and \bar{h}^a , times the population in its corresponding cohort, (P_t^a). Then we sum across age cohorts:

$$H_t = \sum_{a=15}^{79} \bar{E}^a * \bar{h}^a * P_t^a.$$

This total hours worked after 2007 is our counterfactual measure of hours in absence of the Great Recession. Assuming that the employment ratio and average hours worked had not changed, which

is a reasonable assumption given the stability of E_t^a and h_t^a , H_t is the level of hours we would have expected in the economy given only demographic changes, through P_t^a . Figure 19 plots three pieces of data: the linear trend of employment without taking into account demographics³⁰ (gray line), our employment counterfactual, H_t (blue line), and the actual data (orange line). It is evident from Figure 19 that the linear trend of total hours and the data move parallel to each other; in 2015 the gap in between these was -5.8% of the actual hours. On the other hand, the data and our counterfactual measure of employment are converging as the gap in between these is just -0.9% of the actual hours..

Figure 19: Total hours worked



Source: Authors' calculation with data from CPS and Census

We are conscious that the Great Recession constituted an important crisis, generating a big deviation of employment from its pre-crisis trend. However, it is also important to note that demographics play an important role in explaining the reason why employment did not recover to its trend before the crisis. The aging of the working age population implies a fall in the total hours worked, which is captured by our counterfactual employment trend. Comparing the data to this counterfactual employment trend shows that demographics is important in explaining the “slow” recovery in labor.

³⁰This is estimated as the fitted line for the data in between 1990 and 2007, and then using this fitted line to forecast the years after 2008.

Furthermore, it provides evidence that ignoring demographic changes from economic analysis can be detrimental not only for labor supply but for economic activity as a whole.

3.4 Growth Model and Demographics

In this section, we describe a variation of the growth model, in which the representative household is comprised of individuals with different ages. We will use this model to generate our quantitative results, similar to the approach by Hayashi and Prescott (2002) and Chen et al. (2006). Below, aggregate variables are defined by capitalized letters, while per-capita variables are lower-cased.

3.4.1 Households

We assume there is a representative household with N_t members at time t . Population grows at rate $\gamma_{Nt} = \frac{N_t}{N_{t-1}}$. For each t , there is a number of P_t^a members of age a , so that $N_t = \sum_{a=s}^S P_t^a$, where s and S are the youngest and oldest ages in the household, respectively. Also, the household owns capital and rents it to firms. Further, the household solves the following problem:

$$\begin{aligned} & \max_{\left\{ \left\{ c_t^a, h_t^a \right\}_{a=s}^S, K_{t+1}, X_t \right\}_{t=0}^{\infty}} \sum_{t=0}^{\infty} \beta^t \sum_{a=s}^S P_t^a (\log(c_t^a) + \alpha^a \log(T - h_t^a)) \\ & \text{s.t.} \\ & \sum_{a=s}^S P_t^a c_t^a + X_t \leq w_t \sum_{a=s}^S P_t^a h_t^a + r_t K_t - \tau_t (r_t - \delta) K_t - \pi_t \quad \text{for } t = 0, 1, \dots \\ & K_{t+1} = X_t + (1 - \delta) K_t \quad \text{for } t = 0, 1, \dots \\ & \text{given } K_0, \end{aligned}$$

where aggregate consumption is $C_t = \sum_{a=s}^S P_t^a c_t^a$ and aggregate hours are $H_t = \sum_{a=s}^S P_t^a h_t^a$, T is the total time endowment per member, β is the discount factor, α^a is the share of leisure in the utility function for individuals with age a , w_t is the wage rate, r_t is the rental rate of capital, δ is the depreciation rate, τ_t is the tax rate on capital income, π_t is a lump-sum tax.

3.4.2 Firms

There is a representative firm, with the standard Cobb-Douglas Production Function, $Y_t = A_t K_t^\theta H_t^{1-\theta}$, where Y_t is aggregate output, A_t is total factor productivity, K_t is the capital stock rented by the firm,

and H_t is the labor input of the firm measured in aggregate hours. We define θ as the share of capital in output. We assume that A_t grows at rate $\gamma_{A_t} = \left(\frac{A_t}{A_{t-1}}\right)^{\frac{1}{1-\theta}}$.

3.4.3 Government

The government taxes household's income on capital and lump-sum tax π_t , and uses these resources to finance government spending G_t so that the government budget balances every period:

$$G_t = \tau_t (r_t - \delta) K_t + \pi_t.$$

3.4.4 Competitive Equilibrium

The resource constraint of the economy is given by:

$$C_t + X_t + G_t = Y_t,$$

where C_t is aggregate consumption, X_t is aggregate investment and G_t is government purchases.

Given a government policy $\{G_t, \pi_t, \tau_t\}_{t=0}^{\infty}$, a competitive equilibrium for this economy is an allocation $\left\{ \{c_t^a, h_t^a\}_{a=s}^S, X_t, K_t, Y_t \right\}_{t=0}^{\infty}$ and a sequence of prices $\{w_t, r_t\}_{t=0}^{\infty}$, such that:

1. given the government policy and prices, the allocation solves the household's problem,
2. given the government policy and prices, the allocation maximizes firm's profits such that factor prices equal their marginal products, $w_t = (1 - \theta) A_t \left(\frac{K_t}{H_t}\right)^{\theta}$ and $r_t = \theta A_t \left(\frac{K_t}{H_t}\right)^{\theta-1}$.
3. the government budget is satisfied,
4. and the market clearing condition holds:

$$\sum_{a=s}^S P_t^a c_t^a + K_{t+1} - (1 - \delta) K_t + G_t = A_t K_t^{\theta} \left(\sum_{a=s}^S P_t^a h_t^a \right)^{1-\theta}$$

3.4.5 Numerical Solution

We solve the model in a similar manner to Hayashi and Prescott (2002) and Chen et al. (2006). First, we compute the steady state of the U.S. economy in the sufficient distant future, using the calibrated

parameters and exogenous variables. The steady state is obtained from the equilibrium conditions of the model. With this steady state, we apply a shooting algorithm toward this steady state from the given initial conditions, corresponding to the first trimester of 1990. The solution to this algorithm is an equilibrium transition path from the initial conditions to the final steady state.

The equilibrium conditions are characterized by the standard intratemporal condition, Euler equation, and resource constraint obtained from the household's and firm's optimality conditions:

$$\frac{\alpha^a c_t^a}{T - h_t^a} = (1 - \theta) A_t \left(\frac{K_t}{\sum_{a=s}^S P_t^a h_t^a} \right)^\theta \quad \forall a, \forall t, \quad (40)$$

$$\frac{c_{t+1}^a}{c_t^a} = \beta \left[1 + (1 - \tau_{t+1}) \left(\theta A_{t+1} \left(\frac{K_{t+1}}{\sum_{a=s}^S P_{t+1}^a h_{t+1}^a} \right)^{\theta-1} - \delta \right) \right] \quad \forall a, \forall t, \quad (41)$$

$$K_{t+1} = (1 - \delta) K_t + A_t K_t^\theta \left(\sum_{a=s}^S P_t^a h_t^a \right)^{1-\theta} - \sum_{a=s}^S P_t^a c_t^a - G_t \quad \forall t. \quad (42)$$

To obtain the steady state, first we detrend all variables so that $\hat{x}_t = \frac{x_t}{A_t^{\frac{1}{1-\theta}}}$ for per capita variables and $\hat{x}_t = \frac{X_t}{A_t^{\frac{1}{1-\theta}} N_t}$ for aggregate variables. Equations (40) through (42) become:

$$\frac{\alpha^a \hat{c}_t^a}{T - \hat{h}_t^a} = (1 - \theta) \left(\frac{\hat{k}_t}{\sum_{a=s}^S \eta_t^a \hat{h}_t^a} \right)^\theta \quad \forall a, \forall t, \quad (43)$$

$$\frac{\hat{c}_{t+1}^a}{\hat{c}_t^a} = \frac{\beta}{\gamma_{At+1}} \left[1 + (1 - \tau_{t+1}) \left(\theta \left(\frac{\hat{k}_{t+1}}{\sum_{a=s}^S \eta_{t+1}^a \hat{h}_{t+1}^a} \right)^{\theta-1} - \delta \right) \right] \quad \forall a, \forall t, \quad (44)$$

$$\gamma_{At+1} \gamma_{Nt+1} \hat{k}_{t+1} = \hat{k}_t \left[\left(\frac{\hat{k}_{t+1}}{\sum_{a=s}^S \eta_{t+1}^a \hat{h}_{t+1}^a} \right)^{\theta-1} (1 - \psi_t) + (1 - \delta) \right] - \sum_{a=s}^S \eta_t^a \hat{c}_t^a \quad \forall t, \quad (45)$$

where ψ_t is the ratio of government purchases to output, $\frac{G_t}{Y_t}$, and η_t^a is the ratio of the population of individuals of age a at time t to the total population at time t , $\frac{P_t^a}{N_t}$.

In steady state, detrended variables do not grow and the ratio of individuals of any age a with respect to total population remains constant. Hence the steady state equilibrium conditions are given

by:

$$\frac{\alpha^a \hat{c}^a}{T - h^a} = (1 - \theta) \left(\frac{\hat{k}}{\sum_{a=s}^S \eta^a h^a} \right)^\theta \quad \forall a, \quad (46)$$

$$1 = \frac{\beta}{\gamma_A} \left[1 + (1 - \tau) \left(\theta \left(\frac{\hat{k}}{\sum_{a=s}^S \eta^a h^a} \right)^{\theta-1} - \delta \right) \right], \quad (47)$$

$$\gamma_A \gamma_N \hat{k} = \hat{k} \left[\left(\frac{\hat{k}}{\sum_{a=s}^S \eta^a h^a} \right)^{\theta-1} (1 - \psi) + (1 - \delta) \right] - \sum_{a=s}^S \eta^a \hat{c}^a. \quad (48)$$

3.5 Demographics and Macroeconomic Aggregates

3.5.1 Calibration

We calibrate the growth model described above to determine the effects of demographic changes on economic activity in the United States. The time period we use for calibration corresponds to 1990 - 2007. The model has four parameters that are the same for all the household: θ (capital share in production), δ (depreciation rate), β (discount factor), and T (total discretionary hours in a week). Also, there is an age specific parameter (α^a). For our analysis, we shut down the government, so that its revenue and expenditure is equal to zero. The values for the four common parameters are shown in Table 17. These are calculated in the standard way, as detailed in the Appendix.

Table 17: Calibration - Parameters for US Economy (1990 - 2007)

Parameters	Value
θ	0.33
δ	0.058
β	0.948
T	100

The disutility of labor, α^a , is an age specific parameter that is chosen such that the average of hours worked in the model is the same as the hours worked in the data, for each age. Using the intratemporal condition of our model, (40), we obtain:

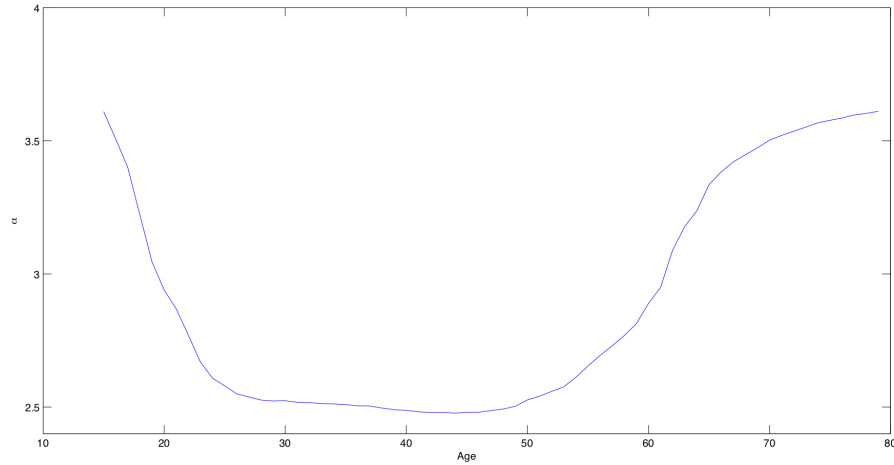
$$\frac{\alpha^i \hat{c}^i}{T - h^i} = \frac{\alpha^j \hat{c}^j}{T - h^j} \quad \forall a = i, j.$$

The Euler condition, (41), implies that consumption level is the same for all ages. As a result, the above equation simplifies to:

$$\alpha^i = \frac{T - h^i}{T - h^j} \alpha^j \quad \forall a = i, j.$$

Using our data counterparts, \bar{h}^a , calculated in equation (39), we calibrate α^a for all a . Figure 20 portrays the values of the disutility of labor by age. Our parameters vary between 2.45 and 3.56. These are higher than what is documented in the literature. The reason for this is that we consider hours per person by age as in Figure 18, and not the average hours worked (as in Figure 17).

Figure 20: Disutility of Labor by Age: α^a



As mentioned before, we are interested in quantifying the effects of demographics on output and labor. We will carry out two experiments. The first only considers the effect of demographics on our model economy and sets up a counterfactual of how macroeconomic aggregates would have evolved

in absence of the Great Recession. Demographics affect economic activity through the population growth rate, γ_{Nt} , and through the ratio of the population of individuals of age a at time t to the total population at time, η_t^a . Both γ_{Nt} and η_t^a are measured using data from the census. Using the solution method described in Section 3.4.5, we use these time series and a constant TFP growth rate $\bar{\gamma}_A = \frac{1}{T} \sum_{t=1990}^{2007} \gamma_{At}$ to obtain the equilibrium path for macroeconomic aggregates³¹. We compare the evolution of the aggregates in our model to those of the data to quantify the importance of demographics in explaining trends in economic activity. Our second experiment builds on the first one by considering demographic effects (γ_{Nt} and η_t^a) along with time-varying TFP growth rates, γ_{At} ³².

3.5.2 Results

The period 1990 - 2015 is a time frame which constitutes a transition from a fast growing population composed of middle-aged individuals to a slow growing population with older individuals. Incorporating this feature into our model, we analyze the transitional dynamics of several macroeconomic aggregates for the pre-crisis period (1990 - 2007) and the years after the crisis (2008 - 2015). As mentioned in Section 3.5.1, at first we only consider these demographic effects, and exclude any other exogenous time varying variables, such as TFP. This allows us to understand how the economy would have behaved in absence of the Great Recession.

The first aggregate we evaluate is the capital to output ratio. There are two effects at work in the demographic transition of this economy. First, the decrease in the population growth rate generates an increase in the consumption per capita over time. Second, the aging of population reduces the amount of labor offered to the market, while keeping constant the number of people consuming. This second effect reduces the consumption per capita over time. These two effects offset each other, as can be inferred from (44). As a consequence of this, our model predicts an almost time invariant trend for the capital to output ratio as can be observed in Figure 21.

³¹For the first experiment's final steady state, we set the population growth to 0.4%, which is consistent with the census's estimation of the growth rate for the period 2050 - 2060. Also, we set the growth rate of TFP in steady state equal to the average growth rate between 1990 and 2007.

³²For the second experiment's final steady state, we set the population growth rate equal to 0.4% and the TFP growth rate equal to the average TFP growth for the period 2008 - 2015.

Figure 21: Capital/Output ratio with only Demographic Changes

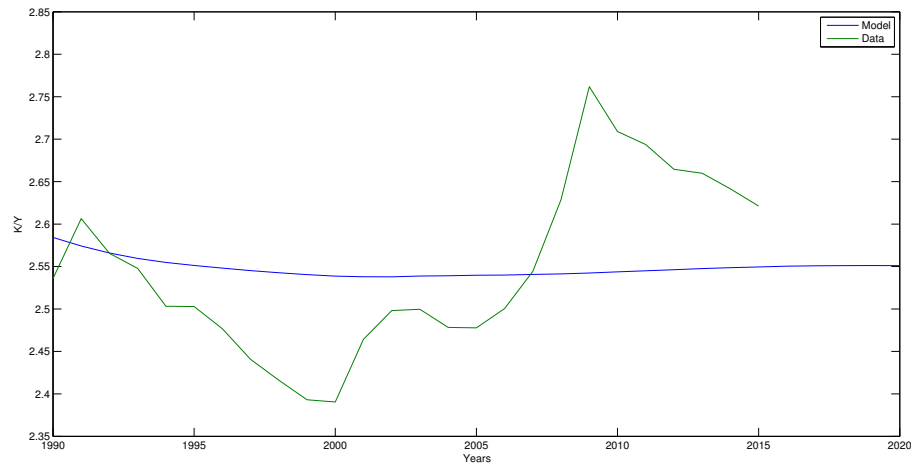
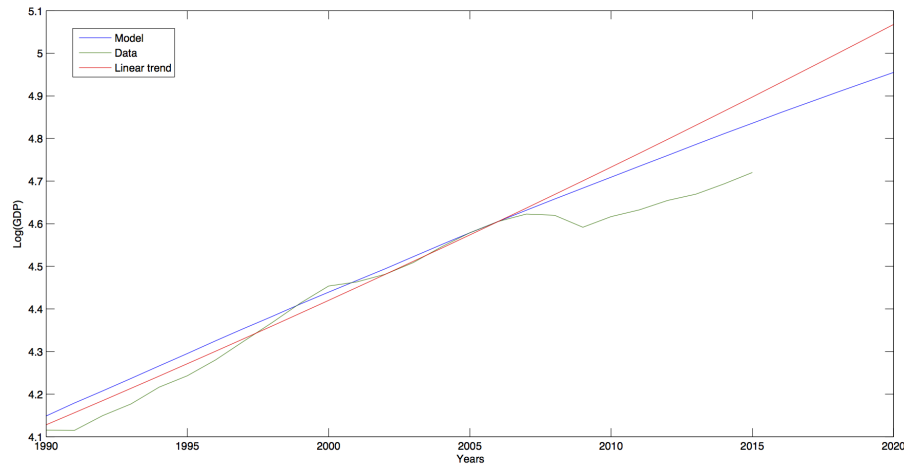


Figure 22 presents the evolution of output in the data since 1990 (green line). It is clear that after the Great Recession, output deviated from its previous trend (red line) and did not converge back to it³³. A model which excludes the demographic changes we account for in our model would yield an output trend similar to the linear trend of Figure 22³⁴. By considering demographic changes, through changes in the population growth rate and the population composition, our model is able explain at least part of the deviation of GDP from its trend previous trend.

³³The linear trend is calculated as the trend of the data from 1990 to 2007.

³⁴We solve our model with constant population growth rate and time invariant population composition, and obtain a output series similar to that of the linear trend.

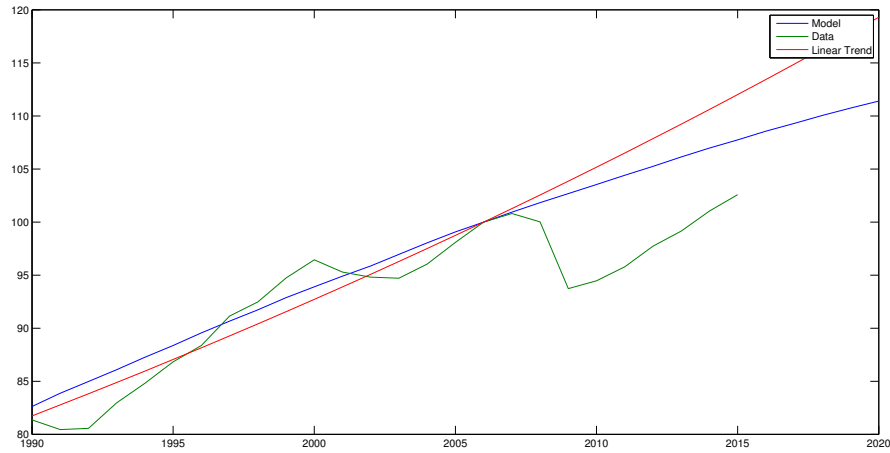
Figure 22: GDP with only Demographic Changes



The model with only demographic changes is not able to account of all of the drop in GDP, as the main contributor of the drop was the Great Recession, which is not modeled in our first experiment. Our exclusion of the negative TFP shock generated by the Great Recession is necessary for us to quantify the only effects of demographics in explaining the deviation of the data from its pre-crisis linear trend. We document that demographics accounts for 35% of the gap in between the pre-crisis linear trend and the data.

The channel through which changes in the population growth rate and the population composition affects output is by the reduction of labor supply. As the population ages, labor supply falls due to reduction in the hours supplied by the older cohorts. Figure 23 is the model counter part of Figure 19. When we compare the model's total hours to the counterfactual employment trend of Figure 19, we can see that the fall of the latter is more pronounced. In the model, demographics only affects labor supply through the intensive margin, i.e. the number of hours supplied by each cohort. The counterfactual employment trend also takes into account the effects of demographics on the extensive margin. That is, older cohorts participate less in the labor force.

Figure 23: Labor with only Demographic Changes



Our second experiment builds on the previous one by incorporating TFP changes also into the analysis. Hence, this model will also account for TFP movements for the time period 1990 - 2015, where the most important was the negative TFP shock of the Great Recession. Figure 24 shows the evolution of the capital to output ratio. We can see that the model does a much better job of capturing the movements in the data. Comparing Figure 24 to Figure 21, we conclude that demographic changes which only affect the economy through labor supply are not able to account for the dynamics in the capital to output ratio. Also, the model predicts a higher level of capital-output due to the decrease in the TFP growth rate³⁵.

³⁵The final steady state was calculated using the average TFP growth rate of the period 2008 - 2015, which is smaller to the growth rate of the period 1990 - 2007.

Figure 24: Capital-output ratio with Demographic and TFP Changes

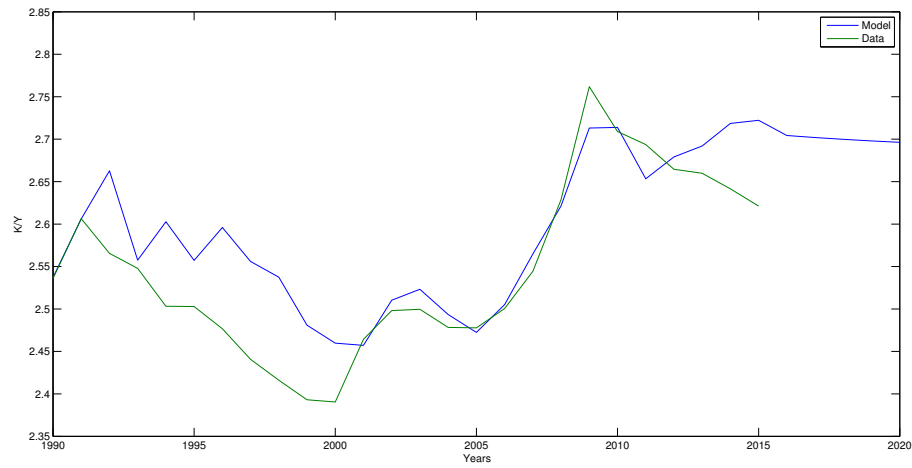
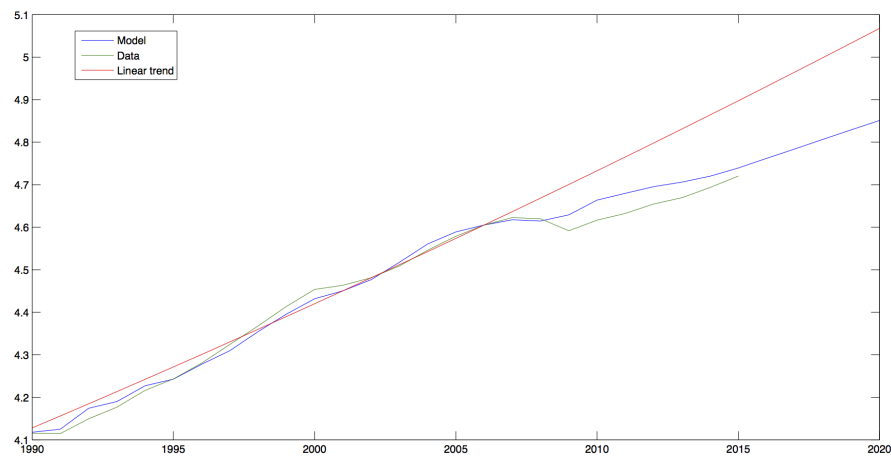


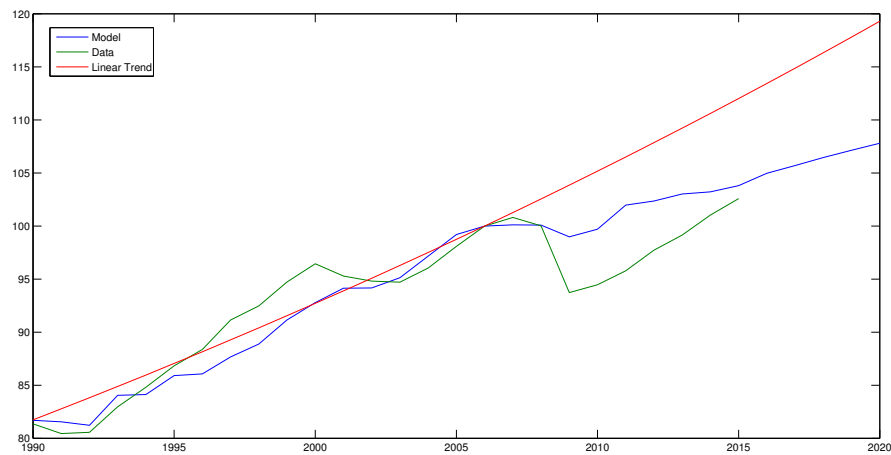
Figure 25 presents the evolution of GDP when we account for both demographic and TFP changes in our model. We can see that the model explains most of the drop in the GDP. Furthermore, by 2015 the gap between our model prediction and the data is only 2.5%. Thus the interaction of TFP and demographic changes do fairly well in capturing the evolution of output for the US economy.

Figure 25: GDP with Demographic and TFP Changes



Demographic and aggregate productivity changes generate a model employment counterpart that has similar movements to total employment hours seen in the data. For example, by adding TFP changes to the analysis, employment in the model falls in the year of the crisis, 2008. This feature was not captured in the previous exercise by construction. By 2015, the gap in between the model and data employment series was of about 1.2%. If our model was able to capture effects through the extensive margin, we suspect that this gap would be even smaller.

Figure 26: Labor with Demographic and TFP Changes



3.6 Conclusion

The effects of demographics may not be big or fast, but they have the potential of being important. The Great Recession coincides with a unique demographic period. At the start of the crisis, the generation of baby boomers started to enter retirement. Even though demographics is not what caused the Great Recession, it has the potential of explaining certain patterns for the slow recovery after the recession. For example, demographics play an important role in total hours worked and GDP not returning to their pre-crisis trend levels. In this chapter, we quantify the effects demographics had on explaining the evolution of output and labor.

We develop a modified version of the standard growth model. This model incorporates demographics into the neoclassical framework through population growth rates and changes in population composition across time. We calibrate this model to test the implications of these demographic

changes. First, we abolish the effects of the Great Recession on economic activity, so that we can evaluate how demographics affected output and labor for the time period 1990 - 2015. We find that the model explains 35% of the between output's pre-crisis trend and the data. We find that labor also drops but not substantially. This is a consequence of demographics only affecting labor through the intensive margin, amount of hours worked. If we considered a framework in which agents decided whether to participate in the labor force or not, then we expect that hours would drop further in the model. When we account for TFP changes for the time period analyzed, we find that the model does a better job of capturing movements in the data, for different macroeconomic aggregates.

It is important to note that our model only considers the effects of demographics on labor supply, which limits the effects of demographics on other variables. For example, we are not considering potential interesting effects of savings decisions by different cohorts that can be important. To evaluate this, a life cycle framework would be more appropriate.

From the policy stand point, we have not assessed the interaction of changes in demographics and government policy. Changes in the composition of the population has implications for tax policy as well as for social security. To understand the impact of demographics on labor tax revenue it is important to carry out an analysis in which demographics not only affects labor supply but also labor productivity, as suggested by Kuznets (1960). For the case of social security, given that the current US system is largely pay-as-you-go, a further analysis should be carried out in order to evaluate the implications of an aging population for both government debt and the sustainability of the social security.

4 Conclusion

The objective of this dissertation is to evaluate the effects of government policies on macroeconomic aggregates. Chapter 1 and chapter 2 study two specific government policies and how these policies impact welfare, employment, aggregate productivity, and output through the resource allocation channel. Chapter 3 analyzes the role of demographics in the current US economy, setting the foundations for policy analysis in the near future.

Chapter 1 studies the effect of occupational licensing on welfare, the allocation of labor, and the wage premium between licensed and unlicensed workers. Occupational licensing affects close to 25 percent of workers in the United States. The social benefits and costs of licensing policy are topics of much debate as licensing has implications for consumer welfare and labor market outcomes. This policy is costly because it acts as a barrier to entry for workers into licensed occupations in the labor market. However, it alleviates an information asymmetry in the market of goods and services. The conventional view of the literature on occupational licensing is that the costs are larger relative to the benefits. But, the assessment of the benefits of licensing has been limited. To tackle this, I developed a framework with adverse selection in the product market and occupational choice in the labor market. There are two productive sectors in the economy. In the licensed sector, the good that is produced is heterogeneous in its quality, which is unobservable to consumers. In the unlicensed sector, a homogeneous good is produced. The information asymmetry in the product market, carries over to the labor market, affecting the occupational choice of heterogeneous workers between sectors. Also, to enter the licensed sector a worker must obtain a license. To do so, the worker pays a fee and undergoes training, which is costly in terms of effort and time. I estimate this model using worker level micro-data and focus my analysis on low-skilled occupations. I find that removing licensing training requirements leads to a 4 percent reduction in consumer welfare. The main forces that drive this result are that although welfare improves as barriers to entry are lower, this is offset by lower quality producers entering licensed occupations. Hence, when we evaluate the welfare implications of licensing it is important to take into account the information asymmetry. In addition, when training is removed, the wage premium falls by more than half.

Chapter 2 examines the effect of corporate income taxes on total factor productivity. Differences in firms' corporate income taxes distort differentially the cost of factors of production. This potentially generates an inefficient allocation of resources across firms, which directly affects total factor productivity. We use Chilean manufacturing plant census data to quantify the potential loss in TFP

arising from the dispersion in effective corporate tax rates. These tax rates differ across firms due to exemptions deductions and deferrals present in the tax code. We directly measure tax rates from the census data and document a large dispersion in these rates even when we control for size, type of entity and other characteristics. Next, we develop and calibrate a general equilibrium model with monopolistic competition, where firms are heterogeneous in their productivity, tax rate, and capital and output wedges, which account for all other distortions present in the economy. We find that TFP increases between 4 and 11 percent when corporate taxes are eliminated. Next, we find that TFP falls when we implement a tax policy in which we eliminate all deductions and deferrals, and hence all firms face the Chilean statutory tax rate. The main intuition for this result is that although there are gains in TFP from eliminating dispersion in the corporate tax rate, this is offset by the fact that the level of the statutory rate increases the dispersion in marginal products, which generates a TFP loss.

Since the Great Recession, output and labor diverted from their pre-crisis long term trends. In chapter 3, we show that demographics is able to explain a significant portion of the gap between the pre-crisis trend and the data, for both output and labor. An important reason why demographics play an important role during the crisis's recovery period is that the Great Recession coincides with the "baby boomers" entering the age cohorts associated with lower levels of labor force participation. Accounting for these demographic changes, we document that labor is converging to a different employment trend. Furthermore, we modify the standard growth model and calibrate it to capture the demographic features of the data for the period 1990 - 2015. Our results show that demographics account for around 30% of the change in the trend of real variables after the Great Recession. The analysis carried out in this chapter lays the groundwork for future research on the interaction of demographics and government policy for the United States.

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Appendix

A Chapter 1 Appendix

A.1 Model

There exists a cut-off ability, $\tilde{a} \in [\underline{a}, \bar{a}]$, such that workers with $a \leq \tilde{a}$ enter sector 1 and workers with $a > \tilde{a}$ enter sector 2. Define $p_1^* = p_1^*(\mu(a), \sigma(a), c_1^*, c_2^*)$ as the equilibrium relative price. This price is determined by the households' demands of good 1 and good 2 and the equilibrium conditions. Earnings in sector 1 and 2 are given by:

$$y_1(a) = \left(\frac{\theta p_1^*}{r} \right)^{\frac{1}{1-\theta}} \left(\frac{r}{\theta} - r \right) \text{ and}$$

$$y_2(a) = \left(\frac{\theta a}{r} \right)^{\frac{1}{1-\theta}} \left(\frac{r}{\theta} - r \right).$$

Define \tilde{a} as the worker which is indifferent between sector 1 and sector 2:

$$\begin{aligned} \left(\frac{\theta p_1^*}{r} \right)^{\frac{1}{1-\theta}} \left(\frac{r}{\theta} - r \right) &= \left(\frac{\theta \tilde{a}}{r} \right)^{\frac{1}{1-\theta}} \left(\frac{r}{\theta} - r \right) \\ \implies \tilde{a} &= p_1^*. \end{aligned}$$

Hence, for workers $a \leq \tilde{a} = p_1^*$, $d(a) = 1$ since $y_1(a) \geq y_2(a)$. On the other hand, for $a > \tilde{a} = p_1^*$, $d(a) = 0$ as $y_2(a) > y_1(a)$.

A.2 Data

A.2.1 License Cost Components

Carpenter et al. (2012) carry out an in depth analysis of occupational licensing for the Institute for Justice. Specifically, they create a database and use it to evaluate the licensing burdens and costs for 102 lower-income occupations across all states and the District of Columbia. These occupations earn less than the national average and are at least licensed in one state. For each of these occupations they gather information on the different measures of licensing burdens at the state level. In particular, they gather information on licensing fees, amount of time spent on training prior to obtaining a license, number of exams, and minimum age requirements.

I use their burden measures of fees and amount of time spent training to back out the fee and opportunity cost components of the license cost in equation (8). For each occupation, I construct averages across states for the license fees and for the training time requirements. I match this data on fees and amount of time spent training to all the licensed workers within my sample from the SIPP data set. On average, the license fees paid by workers within my sample is \$91. According to a report by The Foundation for Government Accountability, licensing boards typically require renewal fees every one or two years. I construct the discounted value of total licensing fees within a worker's lifetime by making three assumptions. First, since my sample includes workers between the ages of 18 and 64 years, I assume that workers on average spend 40 years working. Second, I assume that workers have to renew fees every two years and every time they renew they must pay \$91. Third, I use the calibrated value of $r = 0.003$ to discount future license fees; this value of r implies a discount rate of $\delta = 0.996$. As my model is static, the calibrated value of the fee component, F , corresponds to the per period equivalent of the present discounted value of total fees across a worker's career. To calculate F , I use the following formula:

$$F = \text{PDV of lifetime fees} \times \frac{(1 - \delta)}{(1 - \delta^{(40 \times 12)})}$$

Although the theoretical model is static, including the opportunity cost of training in terms of resources is important as it also acts as a barrier to entry of workers into licensed occupations. Furthermore, this cost also varies with a worker's ability, which is the main distinction between the opportunity cost and the license fee. I use the average amount of time spent training to calibrate T in the opportunity cost component of the license cost. On average, licensed workers in low-skilled occupations train 9.1 months before they enter a licensed occupation. I assume that workers only train once within their working lifetime. Hence, T corresponds to the per period equivalent of the training time requirement, which is calculated using:

$$T = 9.1 \text{ months} \times \frac{(1 - \delta)}{(1 - \delta^{(40 \times 12)})}.$$

A.3 Counterfactual Policy Analysis

A.3.1 Optimal Training

Figure 27: Distribution of Ability and Allocation of Workers - Benchmark vs. Optimal Training

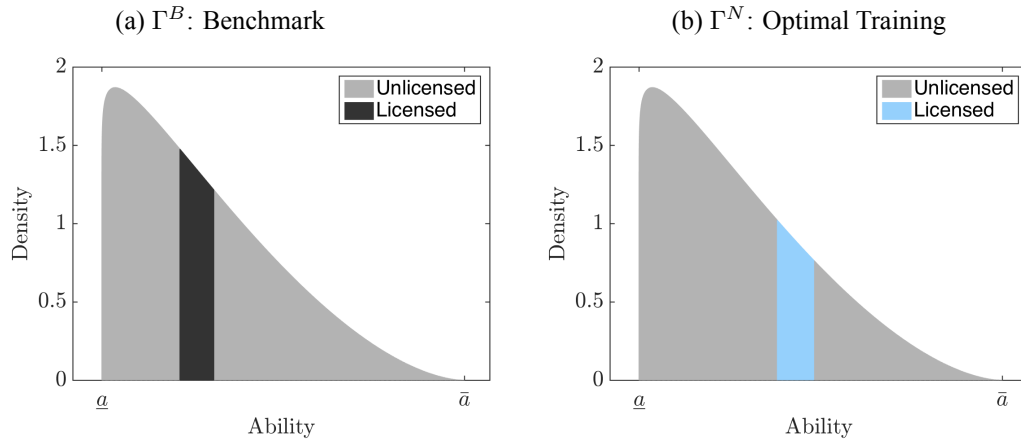


Table 18: Change in Labor Allocation - Optimal Training (%)

Share of Workers $j = 1$	Average Ability in $j = 1$	Average Ability in $j = 2$
-34.3	22.7	-3.2

Table 19: Decomposition of Change in Wage Premium - Optimal Training (%)

Δ Wage Premium	Δ Skill Component	Δ Information Rents
63.5	55.9	7.6

A.3.2 No Fee

Figure 28: Distribution of Ability and Allocation of Workers - Benchmark vs. No Fee

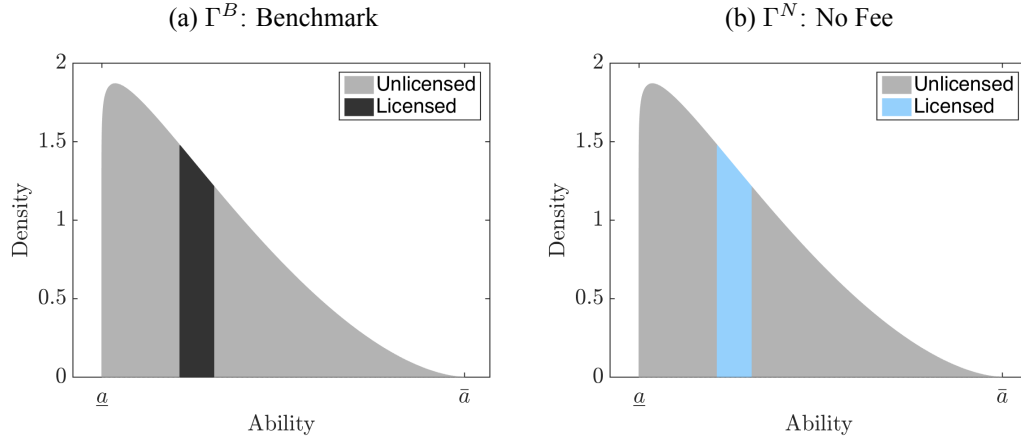


Table 20: Change in Labor Allocation - No Fee (%)

Share of Workers $j = 1$	Average Ability in $j = 1$	Average Ability in $j = 2$
0.1	0.0	0.0

Table 21: Decomposition of Change in Wage Premium - No Fee (%)

Δ Wage Premium	Δ Skill Component	Δ Information Rents
0.0	-0.1	0.1

B Chapter 2 Appendix

B.1 Data

We use the manufacturing sector census data from Chile to construct our sample in the following manner. First, we drop all observations with negative values for output, capital, wage bill, and profit taxes. We believe these negative values are due to reporting error. Our model explains that aggregate TFP is affected by the dispersion of marginal revenue products. For this reason, we trim the 1 percent tails of the observations by the marginal revenue product of capital, $MRPK_{si}$, and the marginal revenue product of labor, $MRPL_{si}$. Then we eliminate the 0.5 percent tails of the observations by physical productivity, A_{si} . Last, when we consider counterfactual flat tax rate policies, there are cases in which some plants have marginal revenue products with negative values, a result that is mathematically possible but theoretically inconsistent. As a result, we eliminate observations with negative marginal revenue products for a counterfactual flat tax rate of 20 percent, which is the highest flat tax level we analyze. If a firm has positive marginal revenue products for this tax rate, then it also does for a lower flat tax rate. On average, the number of firms that are eliminated because of this criterion are only 1.7 percent of the total sample.

Table 22: Number of Plants and Shares in Total Plants by Size Class

Year	Number of Plants	0 - 9 employees	10 - 49 employees	50 - 199 employees	200+ employees
1998	4,530	0.02	0.65	0.25	0.08
1999	4,052	0.06	0.64	0.23	0.07
2000	3,998	0.07	0.64	0.22	0.07
2001	4,214	0.11	0.60	0.21	0.08
2002	4,576	0.11	0.61	0.21	0.07
2003	4,509	0.10	0.60	0.22	0.08
2004	4,726	0.09	0.61	0.22	0.08
2005	4,461	0.11	0.56	0.24	0.09
2006	4,183	0.11	0.55	0.25	0.09
2007	3,919	0.10	0.54	0.25	0.11

The total number of plants in our sample each year ranges between 3,919 and 4,726, as can be seen in Table 22. Between 1998 and 2007, plants with 10 to 49 workers accounted for 60 percent of the total number of establishments, on average. Plants with 0 to 9 workers, 50 to 199 workers, and 200+ workers had an average participation share in the total number of firms of 9 percent, 23 percent, and 8 percent, respectively.

Table 23 presents the representativeness of our sample with respect to the manufacturing sector by size category. For value added, the share of firms with more than 200 employees is 7 percentage points higher in the manufacturing sector than in our sample. On the contrary, this share is 6 percentage points lower in the manufacturing sector relative to our sample for firms with 50 to 199 employees. The representativeness of our sample is better across the three different size categories for employment and the wage bill.

Table 23: Shares of Total Manufacturing Economic Activity - By Size Category

Economic Activity:	10 - 49	50 - 199	200+
	employees	employees	employees
Share of Value Added:			
Sample	0.11	0.26	0.63
Manufacturing Sector	0.10	0.20	0.70
Share of Employment:			
Sample	0.19	0.30	0.51
Manufacturing Sector	0.18	0.28	0.54
Share of Wage Bill:			
Sample	0.14	0.29	0.57
Manufacturing Sector	0.12	0.26	0.62

Notes. This table only analyzes plants with more than 10 employees since those with less than 10 are underrepresented in the ENIA.

B.2 Sensitivity Analysis

Table 24: Output gap decomposition: Hours as Labor Input, $t_{si} = 0$ (%)

Year	Output Gap	TFP Gap	Intersectoral	Intersectoral L	Δ Aggregate
			K		Capital
2001	67.93	14.94	-2.50	2.10	53.38
2002	60.80	14.36	-0.81	1.98	45.32
2003	66.75	14.74	-1.78	3.10	50.71
2004	80.08	23.41	-3.88	3.21	57.39
2005	101.54	31.07	-3.95	2.36	72.02
2006	123.91	33.70	-1.40	13.15	78.42
2007	118.84	32.19	-4.47	4.97	86.14

B.3 Robustness Checks on the Measurement of Effective Tax Rates

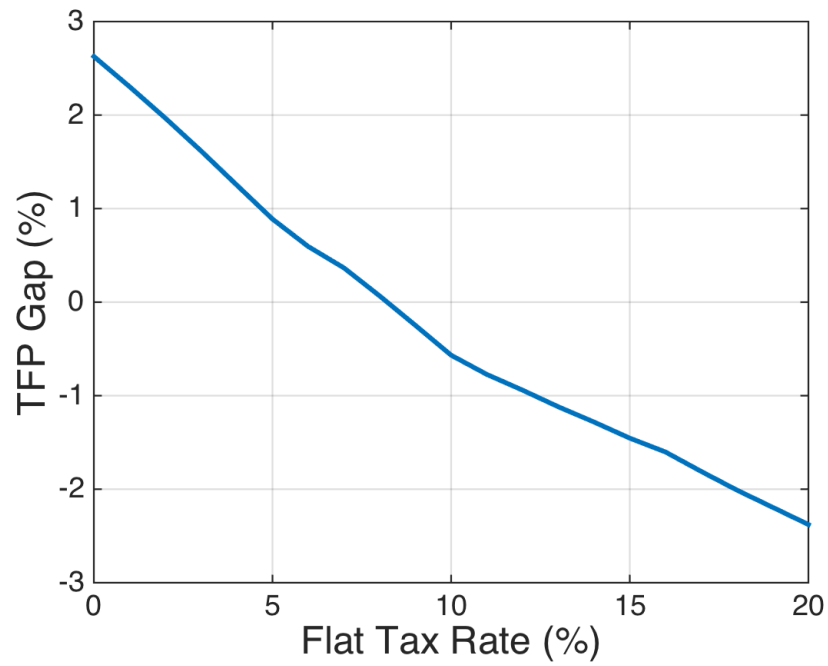
Table 25: Output gap decomposition: Loss Carryforward, $t_{si} = 0$ (%)

Output Gap	TFP Gap	Intersectoral	Intersectoral L	Δ Aggregate
		K		Capital
22.99	6.18	0.78	0.74	15.30

Table 26: Distribution of Effective Profit Tax Rates: Permanent Sample (%)

Year	25th percentile	50th percentile	75th percentile	90th percentile	Statutory Tax Rate	Standard Deviation
2003	2.75	14.46	17.16	24.11	16.5	12.53
2004	8.30	15.56	17.39	22.41	17	11.06
2005	8.43	15.83	17.44	22.36	17	11.52
2006	7.85	15.63	17.31	22.71	17	10.38
2007	8.16	15.87	17.65	24.40	17	13.05

Figure 29: Relationship between TFP Gap and \bar{t} : Permanent Sample (2003)



C Chapter 3 Appendix

C.1 Calibration

To calibrate the model, we use standard methods of Growth Accounting. Parameters δ and K_0 , the depreciation rate and the initial capital are calculated together, so that two conditions are satisfied. We use 1964 as the first data of capital, so any miscalculation of the initial capital is reduced by depreciation over time. First, the initial capital output ratio of the data is equal to the average of the capital output ratio for the first ten years,

$$\frac{K_{1964}}{Y_{1964}} = \frac{1}{10} \sum_{1964}^{1974} \frac{K_t}{Y_t}.$$

Second, the depreciation rate times the average of the capital-output ratio of the model is equal to the average of the ratio of depreciation over GDP in the data.

$$\frac{1}{44} \sum_{1964}^{2007} \frac{\delta K_t}{Y_t} = \frac{1}{44} \frac{depreciation}{Y_t}$$

θ is calculated as the sample average over 1990 to 2007 of the compensation of capital. α^a is calculated for every age with the formula:

$$\alpha^a = \frac{T - h^a}{T - h^b} \alpha^b,$$

such that the hours decided by each cohort matches the sample average of the data. β is calculated using the intertemporal equation 44. T is the total discretionary hours in a week.